Private health insurance in China:

A multilevel examination of its prevalence and distribution, and the impacts on access to healthcare and financial protection

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Declaration

I declare that this thesis has been composed solely by myself and that it has not been submitted, in whole or in part, in any previous application for a degree. Except where states otherwise by reference or acknowledgment, the work presented is entirely my own.

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Abstract

Introduction: The role of private health insurance (PHI) in efforts to achieve Universal Health Coverage (UHC) is a matter of intense academic and policy debate. The government of the People's Republic of China has sought to encourage the take-up of PHI at the same time as expanding the scope of social health insurance (SHI). This study investigates the role that PHI has played in the attainment of UHC goals in China, focusing on its prevalence, impacts on access to healthcare and financial protection, and inequalities in these outcomes.

Methods: The study is based on longitudinal, stratified-sampling data from the China Health and Nutrition Survey. It employs multilevel logistic models to examine PHI prevalence and distribution in the population, and its effects on the utilisation of healthcare, while Heckman selection models and the zero-inflated count models are used to examine its effects on financial protection. It disaggregates the study population to explore inequalities in determinants of PHI prevalence, and access and financial protection attributable to PHI.

Results: Coverage under PHI is unequally distributed, with enrolment higher among individuals of higher socioeconomic status and, at the aggregate level, in the more affluent east and urban areas than in the poorer inland and rural areas. As SHI coverage expanded to cover more of the population against more of the cost of healthcare, and for more treatment types, individuals with coverage under SHI in general became less associated with PHI enrolment than those without SHI. Compared to those without PHI, those with PHI and in need of healthcare was associated with higher utilisation of healthcare, especially in the east and urban areas. However, further analysis finds that this effect PHI was only present where individuals were also covered under SHI. Enrolment under PHI did not confer lower healthcare-related financial risk than those without PHI but covered under SHI, while both PHI and SHI were associated with higher living standards. The effects of PHI on the community varied by geography. In the more developed east of China, higher PHI prevalence was associated with increasingly higher average utilisation for healthcare given increasing need. However, in the less developed inland regions, higher prevalence of PHI was associated with increasingly lower average utilisation given increasing need, and no significant effects on OOP payments.

Conclusions: The study generates several policy-relevant insights. PHI has an inequitable distribution, with socioeconomically advantaged individuals and those resident in more affluent areas more likely to be enrolled. It confers greater access to healthcare for individuals in need of healthcare, from which those living in more affluent areas benefit more. It does not lower financial risk. Since 2004 its prevalence has increased only gradually over time, and as the scope of SHI has expanded, PHI has remained a relatively marginal source of coverage. These conclusions can inform analysis of the appropriate role of PHI in UHC efforts both in China and elsewhere, suggesting that if PHI is identified as a promising route forward, government subsidisations are needed to promote its coverage and strict regulations are required to address the inequalities that it causes.

Lay Summary

This study investigates the role of private health insurance (PHI) in China's efforts to achieve universal health coverage (UHC). Since 2000, China has adopted social health insurance (SHI), a publicly-funded health insurance model, as a means of expanding coverage, but has also sought to encourage the take-up of PHI as a complementary approach. This study uses data from the China Health and Nutrition Survey to examine PHI's prevalence and distribution in the population, its effects on the utilisation of healthcare, and on financial protection. It divides the population into four subpopulations by geo-economic status in China to explore how PHI is distributed across areas with different levels of economic resources.

This study finds that coverage under PHI is unequally distributed, with individuals of higher socioeconomic status and residents in more affluent east and urban areas more likely to be enrolled than others. As coverage under SHI expanded, individuals with coverage under SHI became less likely to have PHI than others. Those enrolled in a PHI scheme were more likely to utilise needed healthcare, especially in the east and urban areas, but only where individuals were also covered under SHI. PHI did not reduce the extent of healthcare-related financial risk faced by enrolees, in contrast to SHI, while enrolment into both forms of insurance was associated with higher living standards. A higher level of PHI enrolment was associated with higher average use of healthcare in communities in the more affluent and economically developed east of the country, but decreased this in the poorer, less urbanised inland areas.

The findings provide information that is useful for the analysis of the appropriate role of PHI in the pursuit of UHC – an important topic in scholarly and policy debates in China and many other low- and middle-income countries. For individuals, coverage under PHI is unequally distributed, and joint coverage under PHI and SHI confers

benefits in terms of higher utilisation of needed healthcare (though not in terms of financial protection). At the community level, it is the more affluent and economically developed east of the country that sees the benefits of PHI in terms of higher overall utilisation. These results suggest that a PHI market is unlikely to generate the broadly equitable access to coverage that is demanded by the UHC ideal.

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Acronyms and Abbreviations

CCA: Complete case analysis. The default modelling approach in many statistical packages in which units with missing values are excluded listwise.

CHNS: China Health and Nutrition Survey. An ongoing longitudinal household survey that commenced in 1989. This is the main data source of this study.

CHARLS: China Health and Retirement Longitudinal Study. Another longitudinal study focusing on people aged 45 or over, starting the nationwide survey in 2011.

CII: Critical Illness Insurance. A complementary public insurance programme to existing SHI schemes in China announced in 2012.

CLHLS: Chinese Longitudinal Healthy Longevity Survey. Another longitudinal household survey focusing on people aged 65 or over, ongoing since 1998.

CMS: Cooperative Medical Scheme. An outdated commune-based rural health insurance scheme in China, updated as New Cooperative Medical Scheme since the 2000s.

CNKI: China National Knowledge Infrastructure. The largest Chinese online academic databases.

CPCCC: Communist Party of China Central Committee. The highest authority of the ruling party in China.

CPI: Consumer price index. A measure of inflation indicating changes in the price level of market basket of consumer goods and services.

FMS: Free Medical Scheme. A government employees' health insurance scheme in China financed by general taxation.

GDP: Gross domestic product.

ICE/FCS: Imputation by chained equations or full conditional specification. A popular algorithm for performing multiple imputation, able to specify different model types for each variable and handle non-monotone missing data.

IIT: Individual income tax. A payroll tax in China.

IPW: Inverse probability weighting. A method to handle unit missingness by weighting units with different propensities for missing.

LIS: Labour Insurance Scheme. An outdated public health insurance in China, covering workers of state-owned enterprises.

LOCF: Last Observation Carried Forward. An ad hoc method of handling missing values.

MAR: Missing At Random. One of three types of missing mechanisms, where the cause of missingness is independent of the unobserved values, given the corresponding observed variables.

MCAR: Missing Completely At Random. One of three types of missing mechanisms, where the cause of missingness is absolutely unrelated to the research questions.

MI: Multiple imputation. A method of handling missing data, based on the assumption of MAR under which the CCA model for the variable with incomplete observations regressed on other conditioning variables is unbiased, applicable to arbitrary missing data patterns, with methods such as data augmentation and ICE/FCS.

MNAR: Missing Not At Random. One of three types of missing mechanisms, where the cause of missingness is absolutely unrelated to the research questions.

MSA: Medical savings account. An individual account of the social health insurance in China for paying the deductible or co-payments, being gradually phased out.

NCMS: New Cooperative Medical Scheme. One of social health insurance schemes in China, covering rurally registered people.

NHSS: National Health Services Survey. An official nationwide survey implemented every five years since 1993.

OECD: Organization for Economic Co-operation and Development. An intergovernmental economic organisation with 36 members, mostly affluent countries.

OLS: Ordinary least square. The estimator used for linear models.

OOP: Out-of-pocket. Used about money that you have to spend yourself rather than having it paid for you, for example by your employer or insurance company, according to Cambridge Dictionary.

PHI: Private health insurance. Insurance operated by commercial insurance agencies to pay indemnity for loss caused by health reasons and medical care.

PPP: Public private partnership. A modality in which governments purchase insurance products from commercial insurers through contracts in the case of this study.

PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses. A guideline for systematic review.

PSU: Primary sampling unit. The sampling unit used in the China Health and Nutrition Survey.

SARS: Severe acute respiratory syndrome. A communicable disease, causing a serious epidemic that happened in China in 2002-2003, forcing the Minister of Health and the Mayor of Beijing to resign.

SCHIP: State Children's Health Insurance Program. The children's health insurance programme in the United States.

SDG: Sustainable Development Goal. The United Nation's global goals of ending poverty, protecting the planet and ensuring that all people enjoy peace and prosperity.

SHI: Social health insurance. A modality of public health financing, characterised by funds contributed through compulsory or semi-compulsory membership for all, with the premium paid or shared by enrolees themselves, their employers and/or the government; the dominant health insurance in China.

SOE: State-owned enterprise.

UEBMI: Urban Employees' Basic Medical Insurance. One of social health insurance schemes in China, covering urban employees.

UHC: Universal health coverage. Access to quality essential healthcare with financial protection for all, a target of the United Nation's Sustainable Development Goals.

URBMI: Urban Residents' Basic Medical Insurance. One of social health insurance schemes in China, covering urban registrants without the Urban Employees' Basic Medical Insurance.

VCE: Variance component estimation. Estimation of variance component of a model, in which the data structure can be specified.

VPC: Variance partition coefficients. An index indicating the proportion of residual variation attributed to a certain level in the multilevel model.

WHO: World Health Organisation. A specialised agency of the United Nations that is concerned with international public health.

ZINB: Zero-inflated negative binomial model. A count model taking into account the chance of zero, based on the negative binomial distribution.

ZIP: Zero-inflated Poisson model. A count model taking into account the chance of zero, based on Poisson distribution.

Table of Contents

Chapter One: Introduction and Background

Universal health coverage (UHC), which means access to high-quality essential healthcare with financial protection for all, is a target of the United Nation's Sustainable Development Goals (SDGs) for global prosperity (United Nations, 2016). Social health insurance (SHI) is a widely-adopted mechanism for reducing financial barriers to care and providing financial protection against the costs, and is commonly framed by governments as a means of achieving the UHC ideal.

Since the beginning of this century, China has experienced a considerable increase in the proportion of the population that has insurance coverage, predominantly under one of a range of SHI mechanisms. This proportion increased from 29.7% in 2003 to 95.7% of the whole population in 2011 (Meng et al., 2012). However, the *depth* and *height* of coverage is still well short of the UHC ideal (with large co-payments and limited benefit packages the norm) (Li et al., 2014) and, in the context of stricter control of the public finances, the government is interested in evaluating the potential for alternative funding strategies such as engaging the private sector to play a larger role in providing insurance coverage (Yip et al., 2012).

In healthcare, private financing generally comes in two forms: private health insurance (PHI) and individual out-of-pocket (OOP) payments[1] (Gu, 2009b). The latter is a key cause of catastrophic health expenditure, the avoidance of which is a key objective of UHC (WHO, 2010a). Thus, the government is interested in encouraging the development of the PHI market, at the same time as expanding the dimensions of coverage under the SHI schemes, in order to reduce OOP payments. Given the lack

[1] This is the situation in China. In other countries, there could be other forms of private financing, such as the community health schemes in India.

of a defined blueprint for advancing UHC, how to define the role of the private sector in health financing is an area of substantial, and polarised, debate (Kutzin, 2008).

Advocates of greater private financing for low- and middle-income countries emphasise the weak administrative capability of the public sector (Preker et al., 2013: 9), the limited public fiscal space for SHI (Scheil-Adlung, 2013: 36), and the greater willingness and ability of individuals to pay for healthcare, compared with those of the government (Preker, 2007: 5). They argue that PHI is, by definition, affordable for those who already find the money for OOP payments for healthcare (Pauly, 2007: 26), and point out that subsidies can help those who cannot afford PHI to access it (Preker, 2007: 5). Thus, they point to the potential for the private sector to increase overall fiscal space (Scheil-Adlung, 2013: 36), reduce OOP payments (Sekhri and Savedoff, 2006) and thereby become a “critical pillar of a robust health financing system” to realise equity, reduce risk and smooth over variations in household income (Preker, 2007: 6).

Contrarily, critics of PHI question private insurers’ efficiency due to their relatively high administrative costs, their lack of bargaining power vis-à-vis service providers, and the tendency for such markets to be highly concentrated (Thomson, 2010). They point out that PHI may actually *decrease* fiscal space for healthcare, since the requirements for subsidisation of privately financed services may compromise the state’s focus on the delivery of essential healthcare (Colombo, 2007: 224-226, Pascall, 2012: 276). They also warn that PHI may not reduce, and can even increase, OOP payments for healthcare due to co-payments and the deductible policies of many products (Bos and Waters, 2008).

Most importantly, concerns regarding equity – in terms of coverage, utilisation, and financial protection – are core to the scepticism around PHI in some scholarly and policy communities (Kutzin, 2013, Thomson, 2010). PHI can be a major source of inequity in countries that rely heavily on PHI (Kutzin et al., 2016). In theory, PHI purchasers are more likely to people with a relatively high income, level of education and employment status. The concentration of PHI among the more affluent may lead to an equivalent concentration of health system resources, to the detriment of equity in service use (Colombo, 2007: 223, 232).

In spite of the international debate, in China policy makers have been keen to explore how best to expand the private sector's role in healthcare financing (State Council, 2014b, China Insurance Regulatory Commission, 2002). As population coverage under SHI has gradually expanded since 2000 (Meng et al., 2012), the PHI market has adapted itself to the new healthcare financing environment by trying to 'fill the gaps' in SHI coverage. As a result, PHI products range from *substitutive* - for those without SHI as an alternative - to *complementary* or *supplementary* for those with SHI (EY, 2016b). The latter (*complementary* and *supplementary)*, which focus on increasing the range of treatments covered and/or the proportion of the payment to be paid by those in receipt of such products, are of particular interest to policy makers, given the expansion of SHI coverage nationwide (Xiang, 2014).

In the specific context of China, there are two fundamental concerns about PHI. First, as SHI has been the principal source of the effort to achieve UHC, the additional role played by PHI is a critical question about the role and future of PHI. Policy makers hope that SHI and PHI can be mutually reinforcing (so that, for example, an increase in enrolment under SHI does not decrease enrolment under PHI) (Xiang, 2014, Liu et al., 2011b). Whether this has proven to the case, however, has not been comprehensively evaluated (Liu et al., 2011b).

Second, while it seems likely that PHI confers benefits for individuals (e.g. in terms of better access to healthcare and financial protection), its impact at the population level is unknown. Enrolment in PHI is determined by factors such as household wealth and education as well as insurers' preference for wealthier (and thus healthier) enrolees (Van de Ven, 2013: 52-53), both of which favour the rich and not those in greatest need. The unequal prevalence of PHI can in turn result in unequal access to healthcare and financial protection across individuals and, in a geo-economically unequal country such as China, across geographies.

in 2015 the government began regional pilot programmes to provide tax incentives to encourage people to purchase PHI (EY, 2016b). Before that, it advocated PHI but did not offer support by using public money (Ng et al., 2012). It is therefore a timely moment to examine the operation of PHI in China and appraise its role in addressing UHC goals. After more than a decade of experimentation with new healthcare financing institutions, much data, including longitudinal data, about SHI and PHI has been accumulated in China. These data provide a key opportunity to conduct such an appraisal.

Accordingly, the primary aim of this study is to contribute to the academic debate on the role of PHI in efforts to achieve UHC objectives, such as more comprehensive and equitable coverage, access to healthcare and financial protection. The study consists in a multi-faceted examination of PHI's effects on these dimensions of coverage in China. It begins by investigating the prevalence of PHI and how this has been shaped by important variables, notably the expansion of SHI, and examines how enrolment is distributed across different socioeconomic strata. The study proceeds to examine how PHI enrolment impacts on access to healthcare and financial protection; in other words, whether and to what extent PHI benefits the enrolees. In addition, the study also examines these impacts at the aggregate level, disaggregating the population by geo-economic region, so that the factors influencing distribution of PHI across regions, and its impacts on coverage, access and financial protection, can be compared.

The following part of this chapter provides more details of the background to this study, locating this in its policy context. The first section presents a brief history of China's changing healthcare institutions. Following this, the key characteristics of the current health financing system (at the time of writing), are outlined, focusing on health insurance, and recent proposals for reform. In the third section, concerns about PHI's effectiveness and inequities are discussed, as a foundation for the literature reviews reported in chapter 2. Then, the research questions are presented. Finally, the structure of the thesis is outlined.

1.1 The modern history of healthcare financing in China

Since 1949, when the People's Republic of China was founded, the health financing system has experienced a number of key transitions linked to broader changes in the nature of economic policies pursued by government. Therefore, three distinctive models can be seen: an initial period of *collectivism* (1950s – 1970s), followed by a period of rapid *marketization* (1980s – 1990s), and a final, contemporary, period of *social insurance* (2000s – present). The brief summary of key developments below is the result of a review of documented administrative regulations, published by relevant government departments such as the Ministry of Health[2], the State Council (the central government), or the Communist Party of China Central Committee (CPCCC), the highest authority of the ruling party in China.

1.1.1 Collectivistic healthcare in Mao's China

Mao Zedong ruled China for 27 years until his death in 1976. Although in his later reign, China experienced a period of social and political upheaval and economic stagnation, the government under his leadership had prioritised social services such as healthcare. In the late 1970s, the share of total healthcare expenditure that came from public spending was always more than 80% (National Health and Family

[2] The Ministry of Health was renamed the National Health and Family Planning Commission, after merging with the Family Planning Commission in 2013, and the National Health Commission in 2018.

Planning Commission, 2013). Most of the population were covered by public health insurance schemes of some form (Liang and Langenbrunner, 2013). The first public health insurance scheme was introduced in 1951 by the *Labour Insurance Regulations* (State Council, 1951), which required state-owned enterprises, or SOEs, to fully subsidise workers to join the Labour Insurance Scheme (LIS), run by the All China Federation of Trade Unions. A year later, the State Council announced the *Direction of Providing Free Medical Care to Staff in Governments, Parties, Organizations and Affiliated Institutions* to mainly cover government officials, public employees and college students (State Council, 1952), which is the precursor of the current government's Free Medical Scheme (FMS). Since all private enterprises were nationalised by government between 1953 and 1956, the state in effect provided all urban employees (and their families in many cases) with public health insurance.

On the supply side, doctors' salaries in all urban hospitals were fully funded by the government. In turn, public hospitals were required to provide healthcare services at very low prices. Due to a shortage of public funding, the government permitted public hospitals to earn extra income by charging a 15% mark-up on prescription drugs and diagnostic tests. At that time, as a result of broadly equitable health insurance coverage, and limited use of expensive medicine and technologies, complaints about the affordability of healthcare were rarely reported (Liang and Langenbrunner, 2013, Blumenthal and Hsiao, 2005).

Things were very different in rural settings, however. The rural health insurance scheme was named the Cooperative Medical Scheme (CMS), which emerged out of village (or commune)-based mutual schemes in the mid-1950s (Li, 2007). In the 1960 policy note, *Direction of Health Services,* this model was formally acknowledged and there were proposals for its expansion (CPCCC, 1960). Financing the CMS therefore relied on numerous small risk funds pooled at the commune level. Every commune member contributed a little to the collective fund in order to access free healthcare afterwards. On the supply side, following the *Report on Focusing Health Services on Rural Areas* (Ministry of Health, 1965), many “barefoot doctors”, who provided primary care while still doing agriculture work, were trained, and commune-funded clinics with one or two formally-trained doctors and 10 – 30 beds were established as a secondary tier of rural healthcare (Daemmrich, 2013).

As a consequence of the degree of state intervention in healthcare financing and delivery, healthcare in China was relatively affordable (individuals only paid about 20% of healthcare costs on average (National Health and Family Planning Commission, 2013)), and there were remarkable improvements in health in the period. Using the common indicators of health outcomes, from the early 1950s to the early 1980s, infant mortality reduced from 200 to 34 per 1000 live births, and average life expectancy increased from 35 to 68 years (Blumenthal and Hsiao, 2005). For its comprehensive coverage and efficiency, the rural CMS was regarded by international agencies to be exemplary – for example, it was recognised as such by the WHO campaign ‘Health for All by the Year 2000’ (Sidel, 1993, Blumenthal and Hsiao, 2015). However, the clinical quality of much of the healthcare provided, especially in rural areas, was often questioned. In particular, rural barefoot doctors were frequently criticised for their very simple techniques and lack of access to modern medical equipment (Li et al., 2012b).

1.1.2 Marketisation of healthcare in the 1980s and 1990s

During the 1980s and 1990s, China initiated a bold programme of economic reforms, with the aim of moving the country’s economic away from central planning towards a more decentralised market-based economy. Its impacts on healthcare included structural reforms, including marketisation and privatisation, along with a significant retrenchment in the role of the state in financing (Blomqvist and Qian, 2008). During this period, central government’s share of total health expenditure in the country fell to just 15%, one of the lowest proportions in the world (Blumenthal and Hsiao, 2005).

On the purchaser side, established insurance schemes were deprived of government financial assistance. In urban areas, the role of state-owned enterprises (SOEs) as the main source of employment for the population diminished, while the role of private enterprises grew. Many SOEs could not afford insurance premiums for their employees, or went bankrupt, while emerging private enterprises rarely purchased insurance for their employees (Blumenthal and Hsiao, 2005). Simultaneously, the collapse of rural communes radically undermined the CMS. By 1993, coverage under the CMS had dropped from about 80% in the 1970s to 6.6% of the population (Liang et al., 2012, Sidel, 1993). The only exception to this trend related to the FMS, the government employees' scheme, which continued to receive stable financing (Ministry of Health and Ministry of Finance, 1989).

On the provider side, the *Opinion on Strengthening Hospital Economic Management Pilots* (Ministry of Health et al., 1979) led to hospital payments based on the number of registered beds rather than the number of registered doctors, as was the case previously. It also required hospitals to focus on financial management. Additionally, the following *Report on Several Policy Issues of Health Reform* (Ministry of Health, 1985) allowed hospitals to charge for services using new equipment or new technologies according to real costs rather than regulated prices. These policies in effect reduced government subsidies to hospitals but granted them greater powers to raise revenues from patients. Since then, prescribing expensive drugs and providing costly services became key channels for increasing hospital revenue, and doctors have received bonuses proportionate to their contributions in these respects (Blomqvist and Qian, 2008). To maximise profits, hospitals encouraged the over-prescription of drugs and the use of expensive diagnostic tests, further increasing patients' financial burden (World Bank et al., 2016). Consequently, in that period, drug bills increased above inflation, and eventually came to account for almost half of total healthcare expenditure in China (Bumgarner, 1992), while lucrative medical technologies such as CT scans became more common (David Banta, 1990).

In rural areas, the government phased out support for “barefoot doctors”, only half of whom were awarded the rural doctor certificate by passing the assessment in the early 1980s. Only trained doctors were allowed to receive income from the CMS (Ministry of Health, 1985), while “barefoot doctors” who had not obtained the certificate turned to selling drugs or quitting medical practice altogether, resulting in a shortage of medical professionals in many villages (Blumenthal and Hsiao, 2005). As coverage under the CMS diminished, healthcare provision shifted from village settings to urban or peri-urban hospitals, most of which charged for services directly, raising financial barriers for many rural residents. As a result, the disparity in healthcare expenditure between urban and rural areas grew from 3:1 in 1981 to 5:1 in 1992 (Hesketh and Zhu, 1997).

In effect, the old public health financing system was dismantled in this period. By 2000, health insurance coverage had fallen to 40% in urban and 5% in rural areas (Yang and Wu, 2014). Simultaneously, the percentage of private healthcare expenditure increased from 20% in 1978 to 60% of total healthcare expenditure in 2001 (Daemmrich, 2013). A process of decentralisation shifted accountability for health financing to the local authorities, while deregulation decreased the authority of state administrations and weakened the capacity of regulators, increasing the influence of healthcare providers who had an incentive to maximise healthcare expenditure (Bork et al., 2011).

In 2003, 50% of people reporting an illness did not visit outpatient care settings, and 30% of patients who were advised by a doctor to receive inpatient treatment did not do so (Yip and Mahal, 2008). In addition, 23.3% of rural households were impoverished by medical expenses in 2004 (Li et al., 2012d). In this context, social discontent and distrust towards healthcare providers increased, leading to public protests and even physical attacks on medical staff (Blumenthal and Hsiao, 2015).

1.1.3 Health reforms in waves since 2000

In 1997, the announcement of *Decisions on Health Reform and Development* (CPCCC and State Council, 1997) marked the new wave of China's SHI institutions. Following the decree, the first scheme, the Urban Employee Basic Medical Insurance (UEBMI), was formally introduced by the *Decisions on Establishment of UEBMI Institution* (State Council, 1998) as a substitute for the former LIS, which had diminished in enrolment and the package of benefits covered over the previous 20 year period. However, the UEBMI expanded slowly in its early stages, until regulations were tightened, especially the introduction of the *Labour Contract Law* in 2008, which enforced the obligation of employers to purchase social insurance for their employees. According to the 2003 National Health Services Survey (NHSS), only 30.4% of the urban population was covered by the UEBMI, while 4% and 4.6% were covered by the FMS and the LIS, respectively (Ministry of Health, 2003).

In January of 2003, the rural New Cooperative Medical Scheme (NCMS), as a new version of the outdated CMS, began its nationwide pilot projects, according to the public document *Opinions on Establishment of NCMS Institution* (Ministry of Health et al., 2003). In conjunction with the NCMS, the government-subsidised Medical Assistance programme for the poorest population, including helping them join SHI, was introduced in rural areas (Ministry of Civil Affairs et al., 2003), and later in urban areas (Ministry of Civil Affairs, 2003). A major catalyst for reform was the severe acute respiratory syndrome (SARS) epidemic in 2002 – 2003, which killed hundreds of people and caused a nationwide panic, forcing the Minister of Health and the Mayor of Beijing to resign, and increasing the pressure on the central government to address weaknesses in the healthcare system and make serious efforts to strengthen it (Liu, 2004).

The Urban Resident Basic Medical Insurance (URBMI) scheme was introduced by the 2007 administrative regulation *Guidance on Carrying out Pilot Projects of URBMI*

(State Council, 2007), as the final brick of the social medical security system to cover the rest of the population uncovered by the UEBMI, the NCMS and the FMS. Thanks to significant government subsidies, the expansion of the URBMI and the NCMS was much quicker than that of the early UEBMI. In 2008, 12.5% of the urban population and 89.7% of the rural population were covered by the URBMI and the NCMS, respectively (Ministry of Health, 2008).

Despite the high rate of coverage, however, in 2008 the inpatient reimbursement rate was only 35.2%, and 14% of households still experienced catastrophic health expenses in a given year (Meng et al., 2012), very high even by developing countries' standards (Li et al., 2014). Partly thanks to an unprecedented stimulus package of $585 billion (13.3% of GDP) to address the 2008 financial crisis (Ruckert and Labone, 2012), China's health system reform programme was upgraded in 2009, with an extra $125 billion earmarked for investing in healthcare in the ensuing three years (Yip et al., 2012). Government health funding doubled to about $157.6 billion between 2009 and 2013, 46% of which went into the SHI or the Medical Assistance programmes (Meng et al., 2015).

Published by the top authority, the *Opinions on Deepening Health Reforms* (CPCCC and State Council, 2009) documents the key tasks of the significant 2009 reform. In it the government acknowledged that contemporary healthcare still failed to satisfy public expectations, due to inequity in resource allocation, weak regulations on medical security, pharmaceutical markets and healthcare providers, insufficient government investment and high OOP payments. Therefore, it notes that future reforms would concentrate on five goals: 1) expanding SHI; 2) increasing public health spending and decreasing regional disparities; 3) building primary care facilities; 4) reforming pharmaceutical markets; and 5) piloting public hospital reforms (Yip and Hsiao, 2009a).

After the 2009 reform, China's public spending as the share of total healthcare expenditure reached 56% and public healthcare expenditure as the share of GDP reached 3% in 2012, compared to 36.2% and 1.8% in 2003 (World Bank, 2018b, World Bank, 2018a). The breadth of coverage increased to 95.7% of the population in 2011 (Meng et al., 2012). The three main SHI schemes, i.e. UEBMI, NCMS and URBMI, cover close to around 87% of the population (Meng and Xu, 2014). The 2009 health reform significantly increased government subsidies for SHI. In 2008, the minimum average government subsidy for the URBMI was ¥80 per capita (¥1≈ £0.11 or $0.14). By 2011, it had reached ¥200 (Yip et al., 2012). The inpatient reimbursement rate rose from 35.2% in 2008 to 46.9% in 2011 (Meng et al., 2012).

The above developments have led to increases in the utilisation of healthcare. From 2003 to 2011, as a percentage of the population, use of outpatient care increased from 13.4% to 14.8%; hospital admissions increased from 3.6% to 8.8%; hospital delivery increased from 73.3% to 95.8%; and the number of self-discharges reduced from 43.3% to 31.8% (Meng et al., 2012). However, unequal access is still evident in some important respects. Taking antenatal visits as an example, an important indicator of maternal and children healthcare, in 2011, 76.8% of urban pregnant women had five or more antenatal visits, compared to 59.0% of their rural counterparts; 78.5% did so in the East, compared to 57.1% in the west and 52.6% in the central regions (Meng et al., 2012). The annual incidence of catastrophic health expenditure also increased over this period, standing at 12.9% compared to 12.2% in 2003 (Meng et al., 2012), suggesting that expanding the depth and height of coverage remains a key policy challenge in the country.

1.2 The current healthcare financing architecture

In China's official statistics, the sources of healthcare financing are divided into three: individual OOP payments, collective payments from all kinds of health insurance, and direct funding by government. Individual OOP payments once dominated total healthcare expenditure in the early 2000s, as noted above. As health reforms proceeded, the shares of the latter two gradually increased (Figure 1.1). In the current years, each of the three sources accounts for roughly one third of total healthcare expenditure. We focus here on expenditure through the insurance mechanisms – public and private.

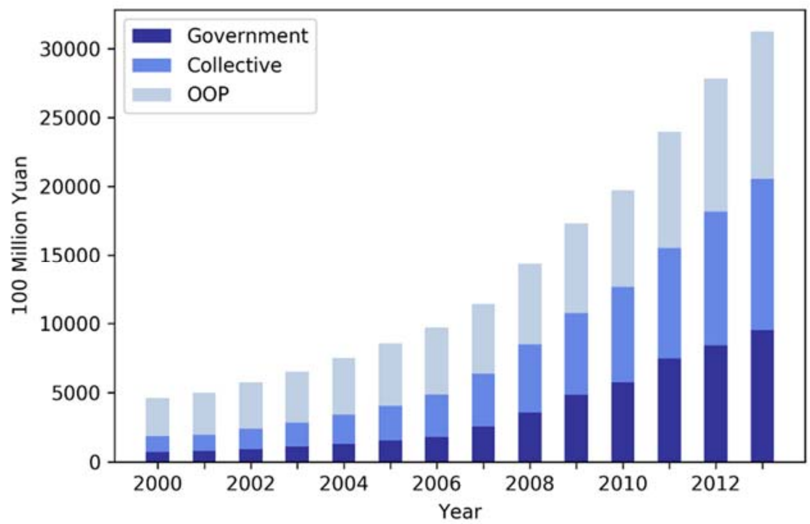

Figure 1.1: The total healthcare expenditure and three main sources of funding healthcare in China. Data source: China Statistics Yearbook 2014; Yearbook of China's Insurance 2014.

1.2.1 Social health insurance

Until 2011, the UEBMI, as a compulsory scheme for urban workers, provided coverage for approximately 265 million people (National Health and Family Planning

Commission, 2013), with an effective average reimbursement rate for inpatient care of 81% (Ministry of Human Resource and Social Security, 2012) (Table 1.1). The employer contributes 6% and the employee contributes 2% of salary, of which all of the employee’s contribution and 30% of the employer’s contribution go to an individual medical savings account (MSA) while the rest goes to a municipal pool, managed by the local bureau of the Ministry of Human Resource and Social Security (State Council, 1998). In 2011, the annual deductible and cap of reimbursement were 10% and 600% (no less than ¥60,000) of the local average salary, respectively (Liang and Langenbrunner, 2013). Healthcare costs under the deductible or over the cap and co-payment can be paid by individual savings in the MSA, and otherwise direct OOP payments. In recent years, the MSA, which has been long criticised for its low efficiency and misuse of funds (enrolees reportedly often draw out surpluses or spend MSA funds on non-healthcare related products), is being gradually phased out (Wu and Wei, 2014).

The NCMS is a voluntary rural health insurance programme, covering 805 million (98.26%) of rural residents by 2012 (National Health and Family Planning Commission, 2013) (Table 1.1). Funding is shared by the enrolee, the local government and the central government, which disproportionately subsidises the NCMS in favour of the poor inland areas (Ministry of Health et al., 2003, Yip et al., 2012). The collected funds are pooled at the county level and managed by local health authorities. MSAs had almost been abolished by 2011. The cap of compensation was 800% of the annual average income of villagers and no less than ¥60,000 (Liang and Langenbrunner, 2013). However, the NCMS is often criticised for its low effective reimbursement rate (<50%) (Liang and Langenbrunner, 2013, Li et al., 2012d), because its compensation policy tilts towards low-tier care providers. In other words, villagers enjoy the highest reimbursement in local village clinics but encounter the highest deductible and co-payments in urban tertiary hospitals. The unequal distribution of high-quality resources often forces rural patients to seek healthcare in urban hospitals, going beyond the NCMS's protection (Liang et al., 2012).

The URBMI is the NCMS's urban counterpart[3], and shares many characteristics. For example, the enrolees are from informal sectors, there is voluntary enrolment and tri-funding comes from enrolees, and local and central governments. There are no MSAs, and so all of the premiums from the URBMI are pooled at the municipal level. The manager is the same as the UEBMI, i.e. the Ministry of Human Resource and Social Security and its local bureaux, but pooled separately. By 2011, the URBMI had covered 272 million people and its compensation cap was defined to be no less than 600% of local residents' annual disposable income and no less than ¥60,000 (Ministry of Human Resource and Social Security, 2012) (Table 1.1). Likewise, its policy is also biased against high-tier services. For example, the annual deductible rose from ¥100 to ¥1000, as the tier of the provider rose from primary to tertiary (Liang and Langenbrunner, 2013). Nevertheless, because health resources are concentrated in urban areas, the effective reimbursement rate of the URBMI (64%) is higher than the NCMS (<50%) (Ministry of Human Resource and Social Security, 2012).

The government's FMS scheme is financed by general taxation, and is not strictly SHI since there are no formal enrolee contributions. Dating back to the 1950s, qualified FMS members are limited to government employees and retirees (employees of many public institutions were also included before 2010), who receive healthcare in appointed hospitals without directly contributing to a medical fund (State Council, 1952). In terms of the compensation rate, the FMS is more generous than other SHI schemes, although this varies across regions and even between employers (Table 1.1). Since the introduction of three SHI schemes, the FMS has gradually been

[3] URBMI's and NCMS's enrolment depend on registered residence in *hukou*, a residency registration system in China, rather than actual residence.

phased out, as more and more government and public institution employees are transferred to the UEBMI (Liang and Langenbrunner, 2013).

Table 1.1 Summary of current public health insurance institutions

	UEBMI	*NCMS*	*URBMI*	*FMS*†
Year of launch	1998	2003	2007	1952
Administration department	Human Resource and Social Security	Health	Human Resource and Social Security	Finance
Target population	Urban employees	Rural registrants	Urban registrants without UEBMI	Government employees and retirees
Pooling level	Prefecture	County	Prefecture	Not Available
Number of pools	333	2852	333	Not Available
Enrolment	Compulsory	Voluntary	Voluntary	Automatic
Number of members	265 million	805 million	272 million	49 million
Individual contribution	2-3% of salary	¥30-50	¥30-50	0
Employer/government contribution	6-8% of salary	¥200	¥200	Not Available
Inpatient reimbursement rate	81%	<50%	64%	90-97%
Outpatient reimbursement rate	Depends on MSA	0-40%*	0-40%*	80-95%
Reimbursement cap	Six-times local average wage	Eight-times local peasants' income	Six-times local disposable income	Varying

Based on 2011 – 2012 data. UEBMI = Urban Employees' Basic Medical Insurance; NCMS = New Cooperative Medical Scheme; URBMI = Urban Residents' Basic Medical Insurance; FMS = Free Medical Scheme; MSA = UEBMI's individual medical savings account.

* An approximate estimate as the coverage of NCMS and URBMI gradually expanded and varied spatially; † compensations varied across regions. These estimates come from some of Beijing's policies for reference only (Beijing Municipal Health Bureau, 1990, USTB, 2009). The data about UEBMI, NCMS and URBMI refer to (Yip et al., 2012, Liang and Langenbrunner, 2013, Meng et al., 2015, Ministry of Human Resource and Social Security, 2012, National Health and Family Planning Commission, 2013).

1.2.2 The private sector

In China, PHI, along with other private institutions, was introduced during the economic reforms in the 1980s. Since then, the Chinese PHI market has developed through three stages, which have been referred to as *germination* (before 1994), *transition* (1994-2003) and *specialisation* (after 2003) (Duan, 2008). In the first stage, due to low income, lack of knowledge of insurance and the remaining coverage of public schemes, PHI prevalence was very low and limited to corporate customers, who bought PHI for their employees. In the second stage, demand for PHI increased and more commercial insurers entered the market. Many products sold in this period provided a one-off indemnity for enrolees after being diagnosed with a critical illness, resembling life insurance (Ng et al., 2012). In 2003, so called 'participating health insurance' [4] was banned by the regulation that aimed at encouraging the PHI market to focus on its core function and played a catalytic role in developing a more specialised market. In 2004, four new specialist PHI companies established businesses in the market (Duan, 2008).

During the 2000s, PHI premiums income steadily increased, while PHI indemnities as a share of total healthcare expenditure increased from 0.3% in 2000 to 1.3% in 2013, and the market over this period also became much more diverse. In 2003, there were only around three hundred PHI products in the market and no specialised PHI companies (Duan, 2008), whereas in 2013, more than one hundred commercial insurers and five specialised companies operated PHI business, providing thousands of products (EY, 2016b).

[4] This form of insurance combined insurance and a dividend-bearing investment; it provided only moderate financial protection but yielded a dividend to consumers.

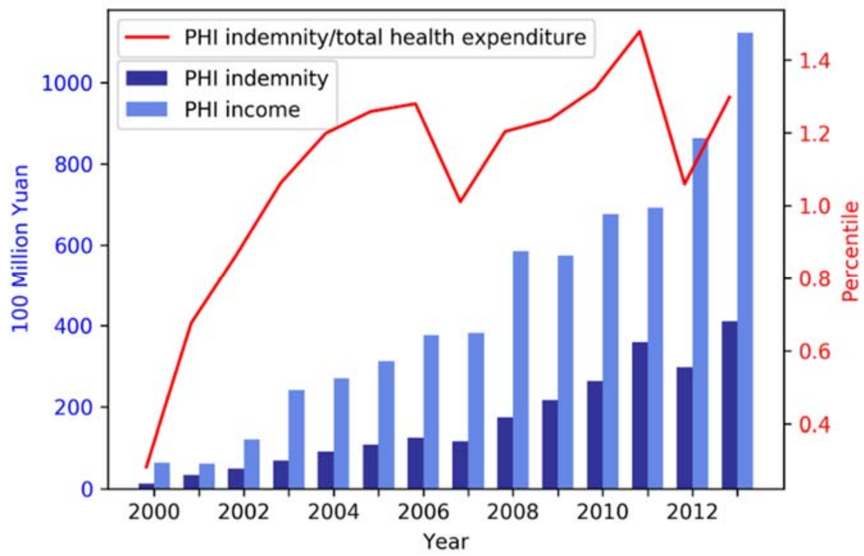

Figure 1.2: Income and indemnities of PHI, and the share of PHI indemnities in total health expenditure in China. Data source: Yearbook of China's Insurance 2014.

In the context of expanding coverage under SHI, many PHI plans provide complementary or supplementary coverage,[5] particularly focused on addressing the caps and co-payment limitations of the main schemes, as described above (EY, 2016b). In this sense, the package of benefits provided by most insurers are similar, usually including protection for critical diseases, compensation for hospitalisation and access to superior amenities. Products are graded and priced according to the array of covered diseases, services and caps, in addition to individual health risks (Ng et al., 2012). The sales of PHI rely heavily on in-house sales staff in local branches of insurance companies, as well as PHI brokers, to facilitate distribution channels. Recent years have also seen increasing sales online (EY, 2016b).

[5] Some products can become substitutive in the absence of SHI, with the increased deductibles and co-payment rates.

1.2.3 Recent policy trends

Government subsidies for the URBMI and the NCMS increased from ¥120 in 2010 to ¥320 in 2014 (Dai et al., 2011, Liang and Langenbrunner, 2013), with the aim of increasing the reimbursement rate of the NCMS and the URBMI to 75% (State Council, 2014a).

To handle the insufficient protection from catastrophic health expenditure (Meng et al., 2012), in August 2012, the central government announced a complementary public insurance, Critical Illness Insurance (CII) (National Development and Reform Commission, 2012). According to its primary design, CII covers no less than 50% of OOP payments exceeding the cap of SHI compensation, generally capped at an annual ¥100,000 at least, though it still has restrictions on certain types of diseases, drugs and services (National Development and Reform Commission, 2012). Interestingly, the plan was to base CII on a public private partnership (PPP), in which governments purchase insurance products from commercial insurers through contracts. The latter gain profits or lose by operating the fund, strictly subject to governments' regulation (Zhao and Ning, 2011). As this programme is still being developed, the related data are too scarce to make effective assessments at the time of writing.

In any case, the gaps in the coverage provided by SHI are likely to remain. In total, OOP payments for healthcare accounted for 33.88% of total healthcare expenditure in 2013 (National Bureau of Statistics, 2014). According to the WHO (2010a), this proportion needs to be reduced to at most 15-20% in order to effectively prevent financial catastrophe and impoverishment. In the last ten years, the absolute value of OOP payments tripled, approximately equal to the pace of increases in disposable income (National Bureau of Statistics, 2014), implying that the financial risk from healthcare has never been mitigated despite enhancements to coverage mechanisms.

As the guideline to current health policy making in China, the 2009 *Opinions on Deepening Health Reforms* proposes a long-term plan to be completed by 2020 with the following essential targets: everyone to receive basic healthcare; multilevel demands in healthcare to be generally satisfied; population health status to improve further (Yip et al., 2012, Meng et al., 2015). To this end, it frames the principal role of SHI as providing “basic coverage”, starting with reducing financial risk from critical illnesses, and gradually extending to covering outpatient minor illnesses. However, SHI packages only partially cover outpatient services, with high deductibles, and insufficiently compensate the costs of inpatient care for critical illnesses - with co-payments, caps and limited covered services and medicines (Yip et al., 2012, Meng et al., 2012, Meng and Xu, 2014). PHI is therefore explicitly framed as providing an important complement to SHI, which is expected to remain a partial source of coverage.

To accelerate the development of PHI, the State Council published *Opinions on Speeding up Development of The Modern Insurance Service Industry* and *Opinions on Promoting Development of Private Health Insurance* in late 2014. According to the interpretation of then Chairman of the China Insurance Regulatory Commission (Xiang, 2014), PHI’s complementary and supplementary role in the national health financing system has been confirmed again by the central government, and a series of preferential policies for PHI are forthcoming. Based on the domestic policy trend and international experiences, he predicted that in 2020 the total PHI indemnity would increase to ¥400 billion, while it was only ¥41 billion in 2013 (Xiang, 2014).

The individual-income-tax (IIT) break policy for purchasing PHI has been piloted in some megacities. This policy provides individuals who buy eligible PHI plans with an annual IIT deduction of up to ¥2400 (usually through the way that employers collectively purchase PHI for employees) (EY, 2016b). Although the effect of this is still too new to assess, a study on the willingness to buy PHI among residents of

Tianjin city showed that higher tax breaks are positively associated with demand for PHI (Zhu and Yu, 2015), suggesting that the policy may be effective in promoting PHI globally.

1.3 Relevant theories and hypotheses

In his seminal paper "Uncertainty and the welfare economics of medical care", Kenneth Arrow points out market failures in healthcare and raises several "problems of insurance" (Arrow, 1963). From then on, a vast theoretical literature on health insurance has been produced (Savedoff, 2004). In addition to basic insurance theories, this research aims to investigate PHI in the context of the UHC movement, progress of which is generally measured in three dimensions: *breadth* (population coverage), *depth* (services coverage) and *height* (costs coverage) (WHO, 2008: 23-28). This section therefore reviews the relevant theoretical research, and make some basic predictions about PHI's operation and impacts in China from the perspectives of the three coverage dimensions.

1.3.1 The difficulties of achieving universal coverage through private insurance markets

Market failures in insurance markets

Expanding coverage *breadth* is key to health insurance schemes that aim to help UHC. Arrow (1963) argues that individuals are normally risk-averse, and would like to insure against the financial risks posed by illness. However, markets in health insurance often fail due to imperfect and asymmetric information between the 'buyers' and 'sellers' in the market, undermining the welfare-enhancing potential of such coverage. In a market for voluntary health insurance, PHI products are bought by consumers on the basis of their *willingness and ability to pay* the market prices (i.e. their demand) (Van de Ven, 2013: 51). In a perfect market (one in which market prices are equal to the social costs of production), the price of PHI is determined by the risk premium *plus* administrative costs *plus* a margin for insurers' expected profit. All else being equal, low-income people are likely to have lower (or zero) demand for PHI at this market price due to their lower (or zero) willingness and ability to pay it. Therefore, even in a perfect market, there is likely to be a socio-economic gradient to insurance coverage.

These problems are aggravated in the presence of market failures. In his paper, Arrow initially raised the concept of moral hazard in this context (Arrow, 1963, Einav and Finkelstein, 2018). He hints a situation in which patients make use of sub-optimally high levels of care, knowing that the direct costs to them of care is limited (or zero); a situation in which physicians prescribe more expensive medication and more intensive treatments knowing the patients under insurance coverage; and a situation in which the insured care less about their health due to their coverage status (knowing that if they fall ill, the financial consequences will be moderated by their insurance contracts) (Arrow, 1963, Einav and Finkelstein, 2018).These types of market failure create upward pressure on risk premiums, thereby reducing demand (Einav and Finkelstein, 2018). There is compelling evidence supports the existence of moral hazard, and insurers usually respond to this through co-payments or deductibles (Einav and Finkelstein, 2018, Sekhri and Savedoff, 2006).

In addition, because insurers have less accurate information about the health status of enrolees than the enrolees themselves, they may set premiums based on average risks across the population (the community rating). However, this premium will be worth paying only for those with above average health risks. Therefore, to ensure that premium income is sufficient to bear the required payments for healthcare, insurers must set the higher premium than the community rating. In practice, to manage *adverse selection*, insurers instead seek to improve their information about enrolees' health, and engage in *risk selection* (or *cream skimming*), providing insurance at different prices to people with different health status (insofar as this can be ascertained) and/or refusing to provide insurance to those with the worst health status (i.e. those with the highest need of it) (Sekhri and Savedoff, 2006). Therefore, the main problem of adverse selection, from the point of view of UHC, is the nature of insurers' responses to it, which have the effect of limiting coverage even further than would be the case in a free market in which information asymmetries were absent.

System-level concerns over coverage of PHI

In theory, the design features of health insurance schemes with objectives set at the system level usually involve large-scale, compulsory contributions to increase revenues, performance-related payments to healthcare providers to improve efficiency, a trend towards larger pooling to enable greater financial security and promote equity, and simplification of benefit packages to increase awareness of entitlements (Kutzin, 2013). However, voluntary, for-profit health insurance schemes that focus their members' attainment of coverage, typically PHI plans, are intrinsically different from those mentioned above in design, and thus may not contribute to UHC objectives, or even undermine equity, at the system level (Kutzin, 2013).

Particularly, in the setting of developing countries, given these differences in design noted above (especially the fact that demand for, and supply of insurance, is likely to be lower for poorer, sicker people due to voluntary purchase), PHI cannot realise comprehensive coverage on its own, and may even compromise the goal of UHC even where an SHI fund is in place (Zweifel and Pauly, 2007: 117). Additionally, a part of the population may be unaware of health insurance due to limited education and insufficient dissemination of insurance information (Van de Ven, 2013: 50). They may also not be able to access it because of geographical factors (Gu, 2009b). Even where it is available, people may be unwilling to trust local commercial insurers because of imperfections in national legislation and a lack of inclusive market institutions and the clear property rights (Pauly, 2007). For commercial insurers, they may find difficulties in operating because of poor licensing standards and regulations for healthcare providers causing the high risk of overtreatment and fraudulent claims (Hsiao et al., 2013: 282).

Despite these problems, in China, PHI is widely regarded in both academic and policy communities as a solution for addressing gaps in SHI coverage (Gu, 2009a, Xiang, 2014). This notion is also popular with developing countries where public funding is limited and the proportion of total health expenditure attributed to OOP payments is high (WHO, 2010b) (suggesting that there should be demand for PHI, given individuals' risk-aversion) (Pauly et al., 2009). Considering some consumers are willing to make high OOP payments, as the alternative insurance is affordable to them in principle (Pauly, 2007: 26).

Possibly as a result of these problems, PHI in China has experienced very slow growth in prevalence, even if the high share of OOP payments in total health expenditure implies the coverage of PHI could have been larger. Theoretically, provided there is no substantial improvement in regulation, the prevalence of PHI is not likely to be sizable enough to complement SHI coverage at the system level.

1.3.2 Health insurance and access to healthcare

In terms of coverage *depth*, health insurance is expected to promote enrolees' access[6] to expensive care that otherwise would be unaffordable or financially catastrophic (Van de Ven, 2013: 51-52), and the access promotion associated with health insurance is theoretically surer than financial protection. Welfare gain from access generated by health insurance has represented the main explanation for the demand for health insurance empirically (Nyman, 2006).

To explore the mechanisms, according to the classic access and utilisation models developed by Aday and Andersen (1974) and Andersen and Newman (1973), access to healthcare is determined by health policies, characteristics of healthcare delivery

[6] The conceptualisation of access in this study is discussed in detail in Section 3.1.2.

system, characteristics of the population as risk, utilisation of services, and consumer satisfaction. At the individual level, insurance coverage influences access as a population characteristic, which financially enable the covered individuals to use additional healthcare.[7] Enabling utilisation of high-quality healthcare and creating stable healthcare demand, health insurance may also benefit healthcare delivery systems through injecting new income streams and thereby helping healthcare providers to improve their supply chains, which lowers costs and raises quality. As a result of improvement of healthcare delivery, individuals' willingness to pay increases (Schellekens et al., 2013: 552).

However, there is a long argument that the enabling power of health insurance may be inefficient because of the moral hazard which generates additional utilisation of healthcare due to price reduction but not need (Pauly, 1968, Einav and Finkelstein, 2018). A debatable point concerns whether, or the extent to which, the additional healthcare used is completely attributable to the moral hazard. Notwithstanding the debate, healthcare is not like common commodities, so the price reduction is effective only for those in need of healthcare. If the additional consumption of healthcare is predominately consumed by those who are ill, it is more likely to result from a transfer of income from healthy to ill – which increasing social welfare – rather than pure price effect (Nyman, 2006).

In China, the high rates of giving up treatment and premature discharge suggest enormous unmet needs (Yip and Mahal, 2008, Meng et al., 2012), while the widespread fee-for-service payment method and persistent incentives for over-prescription among physicians (Blomqvist and Qian, 2008) ensure the existence of the supply-side moral hazard. Thus, the promotion of access can result from either PHI making needed healthcare affordable, or the moral hazard due to price reduction

[7] This model is described with more details in Section 3.2.2.

of PHI. It is worth for the policy maker to distinguish satisfied need from inefficient consumption associated with PHI, if it would like to promote the PHI market.

In practice, access is commonly indicated by utilisation, as an external validation of the former (Aday and Andersen, 1974). The measurement of utilisation comes in the general forms of frequency and intensity (Hou et al., 2014). The frequency indicator, such as visiting a doctor, may be affected less by the moral hazard than the intensity indicator, such as hospitalisation and the length of stay. This is because the literature indicates that the moral hazard mainly happens when consumer demand for healthcare responds to the price (Einav and Finkelstein, 2018); the price reduction effective only for those who are ill represents an efficient income transfer that satisfies need, and the inefficient portion is the costs that ensue (Nyman, 2006). This suggests that the moral hazard usually happens after medical procedures start, when the patient clearly know the price reduction and their real need. Thus, the moral hazard affects utilisation intensity more than frequency.

In addition to the moral hazard, in empirical research, the selection of enrolees may confound the correlation between PHI coverage and access, particularly in China where regulations to restrict risk selection are limited. If adverse selection dominates the enrolment, PHI enrolees would be at higher risk of illness than the general population and thus more likely to use healthcare *per se*. On the contrary, if risk selection dominates, most of high-risk individuals would be rejected or priced out and hence PHI may be associated with less utilisation. The selection principles on insurers' side may be difficult to measure and control for. But on enrolees' side, because PHI purchase is based on capacity to pay and attitude towards insurance, factors that may affect the decision of purchasing PHI such as wealth, education, age and health should be taken into account when investigating PHI's effect on access. Taken all together, should these individual characteristics be well controlled for, in theory, we are likely to observe a positive correlation between PHI coverage and utilisation.

On top of these, it is worth noting that the access gain of the insured may be achieved at the expense of the rest of the population, in effect undermining the equity objective of UHC and aggravated as healthcare resource become scarcer. For example, this problem happens in countries that rely greatly on PHI, such as South Africa and the United States, severer for the former than for the latter (Kutzin, 2013). In terms of China, though insofar there is little evidence about this type of inequity, PHI could bring about the same problem in theory.

1.3.3 Health insurance and financial protection

Relating to coverage *height*, financial protection is regarded as a crucial function of health insurance, because health insurance programmes are basically prepayment mechanisms which pool risks so as to reduce reliance on direct OOP payments for healthcare (Van Doorslaer et al., 2007).

The determinants of total health expenditure and OOP payments are different and vary across countries (Xu et al., 2011). In theory, coverage of health insurance is likely to increase total health expenditure because of utilisation of additional healthcare (Pauly, 1968, De Meza, 1983). Compared to SHI, PHI is even more likely to increase total health expenditure, not only because PHI is more likely to cover higher-cost services, but also because commercial insurers have relatively high administrative costs and a lack of bargaining power against service providers due to their relatively small scale (Thomson, 2010). This inference has been proved by abundant empirical evidence (Colombo and Tapay, 2004, Einav and Finkelstein, 2018).

By contrast, the impact of health insurance coverage on OOP payments is not so clear. Across countries, there is a general trend that OOP payments as a percentage of total health expenditure reduce as average income increases, as wealthier countries rely more on prepayment (WHO, 2010b). However, this does not mean coverage of health insurance absolutely reduces OOP payments, since both total health expenditure and OOP payments could increase as the average income increases (Xu et al., 2011). Some empirical studies report no correlation between insurance coverage structure and OOP payments at the system level (Xu et al., 2011, Colombo, 2007: 218-219).

For individuals, health insurance usually comes in the form of deductibles and varies in benefit packages, which decide the OOP payments that the scheme enrolees must pay (WHO, 2010b) and make the relationship between insurance coverage and OOP payments complex. Additional to OOP payments, the broader concept of financial protection accounts for the living standard as a reflection of the impact of the OOP payments (WHO, 2018). Therefore, some academics apply the ratio of the (OOP) health expenditure to the household (non-food) consumption (or income) as an indicator of the risk of *catastrophic health expenditure* or inversely the level of financial protection of a health system or a health insurance programme (Xu et al., 2003, Wagstaff, 2008).[8]

It is not uncommon to see failures of financial protection of health insurance schemes. For example, more than one studies reported that the NCMS, China's rural SHI scheme, has not reduced the financial risk (Wagstaff et al., 2007, Hou et al., 2014). So has PHI. One reason is that many PHI policies only compensate costs of hospitalisation, while expenditure on drugs accounts for a big share of total OOP payments (Pauly et al., 2009). Additionally, commercial insurers may exclude high-value treatments from the benefit packages of PHI in order to avoid risks, even resulting in an increase of financial risk correlated to PHI coverage, taking Brazil as an example (Bos and Waters, 2008). PHI may also facilitate use of very luxury services with co-payment, effectively increasing OOP payments, like in Yemen, where insurers compete by offering out-of-country treatments (Holst and Gericke, 2012).

[8] This indicator usually goes with a threshold so as to be a binary variable. More details are presented in later Section 3.1.3

As stated in the earlier section, China's PHI supplies concentrate on complementary and supplementary coverage for SHI and compensation for critical diseases, with caps and co-payment policies (EY, 2016b, Ng et al., 2012). However, reportedly less than one fourth of the inpatient care costs of PHI enrolees are in effect reimbursed (Qiu and Chen, 2012). The insufficient coverage of drugs is indeed a problem in China as well (Pauly, 2008). Going back to statistics in Figure 1.2, the increasingly larger gap between income and indemnity of PHI implies that a considerable proportion of PHI money does not go to fund healthcare but become administrative costs and insurers' profits. Taken together, it is possible to observe that PHI fails to reduce financial risk for enrolees.

1.4 The research framework and questions

Given the theoretical problems of PHI in the three perspectives, it is necessary for the policy maker to ask whether shifting a part of the funds that could have been invested in the public sector into the private sector will save money and achieve core UHC objectives (of enhanced coverage, access to healthcare and improved financial protection) more effectively than would be achievable with public delivery alone (Musgrove, 2007: 174). Despite debates over the appropriate role of PHI in the UHC agenda, one point of consensus is that, to meet these goals, PHI needs to highly regulated (Zweifel and Pauly, 2007: 117, Sekhri and Savedoff, 2006). To achieve effective regulation of PHI and a sensible balance between SHI and PHI requires a systematic examination of PHI's role in the health system.

1.4.1 The framework for examining PHI

This study sets out in the basis of the insurance theories reviewed above, the three-dimension coverage model that describes UHC objectives (WHO, 2008: 23-28), and the principle of equity that the WHO and the World Bank emphasise in monitoring the progress towards UHC (i.e. these coverage benefits should be distributed equally in the health system (Boerma et al., 2014)).

A primary focus, therefore, concerns the *prevalence* of PHI studies, i.e. the proportion of the population with such coverage, since the theory predicts the difficulty in its expansion. It may be argued that the higher the level of coverage under PHI, the greater its contribution to the UHC ideal. However, the distribution of PHI across individuals and geographies with different levels of economic resources is also of crucial policy significance. For example, if there is a concentration of PHI coverage among the more affluent, this may result in a concentration of health spending – and thus healthcare resources (staff, supplies, medicines etc) – among the better off and at the expense of the poor. In South Africa, for example, the prevalence of PHI is just 16%, yet PHI expenditure accounts for 42% of total health expenditure (Kutzin et al., 2016). The entire population is entitled to use public facilities, but these are over-crowded and under-resourced in comparison with the providers who serve insured patients. Hence, both the prevalence and distribution of PHI are important considerations for policy makers.

Other crucial concerns are the impact of PHI on utilisation of healthcare (which can be taken as an indicator of the more abstract concept of 'access') (Gulliford et al., 2002) and financial protection. The significance of the findings on the prevalence and distribution of PHI depends, in large part, on what benefits, in terms of access and financial protection, enrolment under a PHI plan actually affords to the enrolee. However, the theory raises questions about realisation of these benefits, especially financial protection. In addition, if enrolment is concentrated among the wealthy then, from an equity point of view, it is clearly more problematic if, as in South Africa, this leads to greater inequity in the allocation of resources (Kutzin et al., 2016). Furthermore, because of the concentration of China's wealth in the large urban centres and the east of the country, it is also important to consider how the distribution and the effects of PHI, in terms of resource allocation, vary across regions (Liu, 2005, Yip et al., 2012). It is therefore important to consider the impacts of PHI at the aggregate level.

1.4.2 Gaps in the literature and the research questions

This thesis is founded on a review, underpinned by a systematic search strategy, of the literature on PHI in China. This review is presented in the second chapter of this thesis and focuses, in line with the above, on the prevalence and distribution of PHI, and its impacts on utilisation of healthcare and financial protection. It is shown in this review that the evidence base is weak, especially in relation to the issue of inequity (in coverage, access, financial protection) that is so core to the UHC agenda. The evidence is especially limited in terms of aggregate-level analysis, despite the fact that spatial disparities in economic resources are acknowledged to be one of most serious social problems in the country (Liu, 2005, Liu et al., 2003, Shi et al., 2010). In addition, only a few studies examine the development of the PHI market in the context of SHI expansion, and thus the interactions between public and private sources of insurance coverage are understudied. To address these key gaps, the current study systematically investigates the distribution of PHI across individuals and regions with different levels of economic resources, and the impacts of this on the distribution of healthcare resources in the country – i.e. measured by the impact of PHI on the utilisation of and financial protection from the costs of, healthcare. Therefore, the over-arching research question is:

> *What role has private health insurance played in meeting universal health coverage goals in China during the period of the scale up of social health insurance?*

This study sets out to answer this question by looking at the prevalence and distribution of PHI (Chapter 5), and the effects of enrolment on access to healthcare (Chapter 6) and financial protection (Chapter 7). Inequities are a key focus of the study and, as the literature review suggests (Section 2.4.2), a multilevel examination and disaggregation of the research population is required to explore inequity properly.

Consequently, the following subsidiary research questions are addressed in the thesis:

Prevalence and distribution

1. How has the prevalence of PHI changed over time?
2. What are the individual and regional determinants of the prevalence of PHI and how have they impacted on the distribution of PHI?
3. How have the effects of these determinants varied across different regions in China?
4. What are the relationships between enrolment under an SHI scheme and PHI enrolment, and how have these relationships changed with the growth of SHI?

Access to healthcare

5. How has PHI impacted on access to healthcare among its enrolees?
6. How has PHI 'complemented' SHI in terms of providing additional access to healthcare for covered individuals?
7. How do the effects of PHI on healthcare access vary across regions?
8. What is the impact of PHI on average access to healthcare in each local context?

Financial protection

9. How has PHI affected the level of direct out of pocket payments incurred by healthcare users among its enrolees?
10. How has PHI 'complemented' SHI in terms of providing additional financial protection for covered individuals?
11. How do the effects of PHI on financial protection vary across regions?

12. What is the impact of PHI on the average level of financial risk in each local context?

1.5 The structure of this thesis

This thesis consists of eight chapters. Chapter Two presents the findings of a literature review, underpinned by a systematic search methodology, on PHI's prevalence, effects on access to healthcare and financial protection, echoing the WHO's coverage model (Section 1.3.2). This literature review shows that, since the early 2000s, premium income for PHI providers and the overall prevalence of PHI have gradually increased over time. The evidence about the impact of SHI on PHI prevalence and the impacts of PHI on access and financial protection is limited, and the results are mostly mixed. The evidence on inequalities in PHI coverage or the effects of those inequalities on access and financial protection are particularly limited. At the end of the literature review, the research gaps are identified, and the research questions are stated again.

Chapter Three outlines the conceptual framework for the study. In this chapter, the key concepts of the study are specified and their translation into operational variables is explained. This consists of 1) the conceptualisation of outcome measures and determinants (or controls), 2) a description of the selected dataset, the China Health and Nutrition Survey (CHNS), and 3) details of how variables have been operationalised.

Chapter Four outlines the analytic strategies of the thesis, based on the statistical package *Stata*. Initially, this provides a brief description of the approach to data manipulation, in which the raw data and the original variables from the CHNS were operated by merging, recoding and transforming to generate the key variables. Following data manipulation, there is a section on missing data – a serious problem for the CHNS as well as many other datasets. The method of handling missing data is explained, and the parameters of its application are presented. Finally, the statistical methods are stated.

The remaining parts of the thesis consists in three results chapters and one discussion chapter.

Chapter Five investigates PHI prevalence and how this has been shaped by the expansion of the SHI programmes. There are two key findings. First, the study finds that, after a reduction between 2000 and 2004, the prevalence of PHI gradually increased. As the breadth and depth of SHI coverage expanded, individuals with coverage under SHI became less likely to have PHI than those without SHI. Second, the study finds that coverage under PHI is unequally distributed, with enrolment higher among individuals of higher socioeconomic status and, at the aggregate level, in the more affluent east and urban areas than in poorer inland and rural areas.

Chapter Six investigates PHI's effect on healthcare utilisation (as an indicator of access). It finds that, compared to those without PHI, those with PHI and in need of healthcare have a higher utilisation of healthcare. However, further analysis finds that this effect of PHI is only present where individuals were also covered under SHI. This effect tends to be weaker in the poorer inland and rural areas than the richer east and urban areas. Furthermore, for a whole community, in the more developed east of China, higher PHI prevalence was associated with higher average utilisation of healthcare as the level of need increased, but in the less developed inland regions, the higher PHI prevalence was associated with increasingly lower average utilisation as the level of need increased.

Chapter Seven investigates the effect of PHI on OOP payments for healthcare. It shows that enrolment in a PHI scheme is associated with neither reduced nor increased OOP payments. By contrast, enrolment into some SHI schemes, such as the government's FMS and the rural NCMS, reduced OOP payments for healthcare to some extent. There is no evidence that PHI and SHI impacted each other's performance on financial protection. For a whole community, a greater PHI prevalence was positively associated with a higher average chance of zero OOP spending on healthcare in the most affluent urban east, while there was no such correlation in other areas.

Chapter Eight, the final chapter, summarises the main findings. It concludes that PHI has an unequal distribution, which is also reflected in inequality in utilisation and financial protection. This study therefore provides new insights into the inequalities that arise from PHI, including by extending the scope of analysis from the individual to the aggregate level. Practically, these issues call for new regulatory actions from government to protect health equity. The findings also indicate that PHI's complementary role is likely to diminish with the continued scale up of SHI.

Chapter Two: Literature Review

This chapter presents a review of the empirical literature on private health insurance (PHI) in China, with a focus on studies of its prevalence, distribution, and effects on utilisation and financial protection during the period of the scale up of social health insurance (SHI). The review is based on a systematic search of all empirical studies published on these topics between 2000 and 2017. Section 1 (below) describes the methods adopted of the review. Section 2 presents the results of the review[9], and Section 3 summarises the findings, and reflects on key gaps in the existing literature.

2.1 Methods

2.1.1 Key concepts

PHI refers to "insurance operated by commercial insurance agencies to pay indemnity for loss caused by health reasons and medical care" (State Council, 2014b). In this review, 'prevalence' refers to the proportion of people in a population covered by PHI. Most previous studies of prevalence have framed this as an indicator of "demand" – i.e. the willingness and ability to pay for PHI. Many studies have examined the determinants of demand – including SHI insurance status and socioeconomic characteristics – which speak to our interest in the interaction between PHI and SHI and distribution of prevalence, respectively. Other studies have used insurers' income from PHI plans as the main indicator of demand, which is clearly different to prevalence. As a multifaceted concept, 'access to healthcare' is difficult to measure,

[9] The literature review does not present the results about the traditional individual socioeconomic determinants of PHI such as wealth and education, because evidence for the correlation between PHI enrolment and high socioeconomic status is abundant theoretically and empirically, and this study focuses on the impacts of SHI and China-specific factors.

and therefore ‘utilisation of healthcare’ is the main indicator used. At the individual level, utilisation mostly refers to an individual’s use of particular kinds of healthcare, though in some studies it is measured by length of hospitalisation. At the aggregate level, utilisation is measured by the total number of visits to healthcare settings among a certain population, and/or, again, the average length of hospitalisation. The concept of ‘financial protection’ is measured in a wide range of different ways. The incidence of catastrophic health expenditure (which examines the impact of household health expenditures on their ability to pay for other basic needs, such as food, housing or education) is commonly studied (Xu et al., 2007). The scale of out-of-pocket (OOP) payments is also a frequently used indicator of financial protection (Van Doorslaer et al., 2007). Some studies investigated the impact of PHI on total healthcare expenditure before compensation from health insurance, for which better data is sometimes available, and which should, in principle, be interpreted separately from data for OOP payments.

2.1.2 Search strategy

The PRISMA guidelines for systematic reviews (Moher et al., 2009) were adopted in designing the search for peer-reviewed literature in both English and Chinese, using the digital library of the University of Edinburgh. Three databases were selected: Web of Science (all databases), PubMed, and the China Knowledge Resource Integrated Database (CNKI), which is the largest, and most frequently updated database of Chinese-language academic publications. The commonly-used medical literature database, Medline, has been included in both Web of Science and PubMed. The search in CNKI was limited to the core journal database, which is a group of peer-reviewed Chinese journals that have been certified as being of high academic quality by one of most authoritative standards developed by the Peking University Library (Peking University Library, 2015, CNKI).

The phenomenon referred to as 'private health insurance' in this thesis has three synonyms in English: private medical insurance, commercial health insurance, and commercial medical insurance. Accordingly, in searching the Web of Science and PubMed, all four were used. In Chinese, the terms *shangye Jiankang baoxian* and *shangye yiliao baoxian* are used to refer to PHI, and both were included in searches of the CNKI database. For the two English-language databases, the keyword "China" was combined with each of the four search terms; while for CNKI this was unnecessary.

For prevalence, the search terms were "prevalence", "demand" and "coverage" in English, and "*xuqiu*" (demand) or "*fugai*" (coverage) in Chinese.[10] For access, the search terms were "access" or "utilisation/utilization" in English, and "*keji*" (access), "*fuwu shiyong/liyong*)" (service utilisation), "*fuwu xuqiu*" (service demand), "*jiuyi*" (using medical care) or "*zhiliao*" (treatment) were used on the CNKI.[11] For financial protection, the search terms "expenditure", "expense", "spending", "payment" or "cost" were used on the English language databases, while "*zhichu*" (expenditure), "*huafei*" (a less formal synonym of expenditure), "*feiyong*" (cost), and "*jingjifudan*" (financial burden) were used on the CNKI.[12]

Because there were too many search terms to be applied together in a single inquiry, this task was divided into three parts according to the key research foci identified

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[10] The translation of "prevalence" into Chinese is rarely used on PHI in the literature. Nearly all papers used "*xuqiu*" (demand).

[11] "Utilisation" is translated as *"shiyong/liyong"* in Chinese. However, they are used too broadly and frequently in Chinese to narrow the search scope. After referring to the included studies for the literature review on all aspects of PHI in China for my first-year board review, I found the combination of *"fuwu"* (services) *"shiyong/liyong"* was often used in relevant papers as a technical term in health economics. However, the term is not straightforward in Chinese and is hardly used in everyday speech. One study used *"fuwu xuqiu"* (demand) to refer to the use of healthcare. More commonly, *"jiuyi"* (using medical care) and *"zhiliao"* (treatment) are formal words in health-related literature. Consequently, I used all of them in the search.

[12] The choice of Chinese search terms referred to my first-year board review as well.

above, i.e. 1) the prevalence of PHI in China, 2) the effect of PHI on access to healthcare in China, and 3) the financial protection afforded by PHI in China. The search strings used in Web of Science are presented here as an example of the searches used across the listed databases:

> Search One: TS = ((health OR medical) AND (private OR commercial) AND (insurance china) AND (prevalence OR demand OR coverage));
>
> Search Two: TS = ((health OR medical) AND (private OR commercial) AND (insurance china) AND (utilization OR utilisation OR access));
>
> Search Three: TS = ((health OR medical) AND (private OR commercial) AND (insurance china) AND (expenditure OR expense OR spending OR payment OR cost)).

In addition, the citations of the included papers were scanned. If an article with a relevant title was cited but not identified in this search, it was added to the final review list after checking its eligibility using the criteria below.

2.1.3 Inclusion criteria

The titles and abstracts of all of the studies identified by these search strings were scanned. The first criterion for inclusion of a study was that it reported empirical data in relation to at least one of the key research foci, as outlined above (i.e. the prevalence, or related effects of PHI in China). In addition, only outputs that provided full information about the methods employed by the study were included. Studies based on tertiary data (i.e. those derived from other studies' outcomes of analysing primary or secondary data) were not included, in order to avoid evidence from the same study being cited repeatedly. Due to the focus on empirical data, editorials, commentaries, meeting abstracts, book chapters and discursive articles were not included. After removing duplicates, a group of 46 studies were included in the review. For details of the searches and data selection, see Figure 2.1 below.

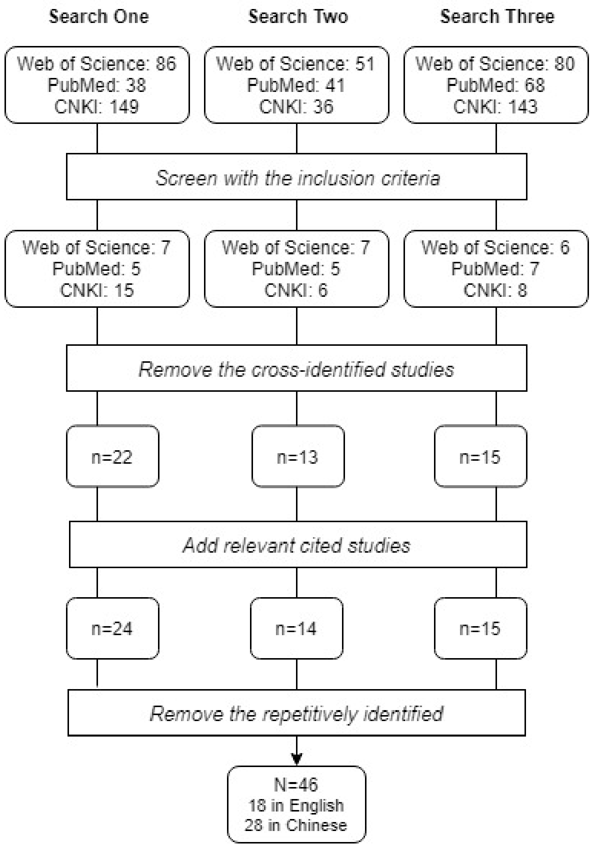

Figure 2.1: The flowchart of the systematic searches and selection.

2.2 Results

2.2.1 Characteristics of the reviewed studies

Of the 46 reviewed studies, 24 examined the prevalence of PHI, 14 examined the effect of PHI on health access, and 15 examined the financial impacts of PHI. Obviously, some studies were cross-identified by these searches. 18 were published in English journals, and 28 were published in Chinese journals.

35 were focused on the individual level, and most used secondary data extracted from large nationwide-sampled surveys. Among them, nine used the China Health and

Nutrition Survey (CHNS), an ongoing longitudinal household survey that commenced in 1989; five used the China Health and Retirement Longitudinal Study (CHARLS), a longitudinal study focusing on people aged 45 or over, ongoing since 2008 (the nationwide survey started in 2011); four used the Nation Health Service Survey (NHSS) data, an official nationwide survey implemented every five years since 1993 (but only in relation to one province); two selected the State Council URBMI Household Survey [13], ranging from 2007 to 2010; one selected the Chinese Longitudinal Healthy Longevity Survey (CLHLS), another longitudinal household survey focusing on people aged 65 or over, ongoing since 1998. The other individual-level studies used data from *ad hoc*, one-off surveys, most of which gave primary data.

Eleven studies were based on data at the aggregate level. The most popular data source, used by ten reviewed studies, was the state administrative statistics provided by the official statistics department focusing on provincial-level data. Another used aggregate data from the NHSS, which provides the county-level data summarised from the individual data.

In terms of the time and scope of data, except for one study looking at the 2003 NHSS county data, all other aggregate-level studies examined longitudinal data. By contrast, 13 individual-level studies examined longitudinal data, and the other 22 examined single cross-sectional data. Except for the four which only investigated one province of the NHSS data, the open survey databases, including CHNS, CHARLS, NHSS, the URBMI survey and CLHLS as well as the provincial-level administrative statistics, conducted sampling in multiple provinces of China. For these one-off surveys, the scope of data collection varied depending on the objectives of the studies. In principle, those results that rely on nationwide data have higher reliability and generalisability than those rely on small-scale surveys, and those that rely on longitudinal data have

[13] URBMI refers to Urban Residents' Basic Medical Insurance, an urban SHI scheme; this survey only includes urban data.

more power than cross-sectional studies, because they can better control endogeneity caused by time-invariants and unobserved individual differences.

Methodologically, a majority of extracted results are from 37 studies that employed regression models as their principal methods of data analysis, adjusting individual or/and aggregate background factors to various extents. Generally, these regression models include basic logistic/probit or linear models for cross-sectional data, and fixed effects, random effects or dynamic models for longitudinal data. Some studies introduced instrumental variables to treat endogeneity. Some studies added difference in difference estimators to extract policy effects by comparing treatment and control groups. A few studies used the Heckman models or Two-part models to handle sample selection. In principle, those that used these techniques should be better at controlling endogeneity problems than others that did not use any.

The other few results that are not derived from regression models are mainly based on calculation of some previously established indexes, such as the Kakwani index, to measure financial inequity. A small number of results are given by comparing population groups with the simple Chi-square tests, which may be biased because of unmatched or uncontrolled individual characteristics correlated to the outcome measures.

In sum, as analysed above, these studies seem to differ in the reliability of data and the validity of methods. Additionally, the measurements that they used, even for the same theme, are so varied. This suggests that it is difficult to extract the results and aggregate them like meta-analysis, which is also not the purpose of this literature review, which aims to identify research gaps for the overall study. Thus, instead, I present them in a narrative way and add my evaluation of their quality based on data and methodologies that they used, referencing relevant previous literature (Acharya et al., 2013). Because few of these studies examined experimental data, and most of them relied on regression models, this literature review primarily uses associational language to describe the results. Causal inferences based on them needs to be cautious. Generally, those that are methodologically superior and hence can control for other variables better should be better at implying causality. For the full bibliographic information, see Appendix A.

2.2.2 Prevalence

Overall trend

The estimated prevalence as the sample mean of people covered by PHI varies among studies using different datasets, and few studies explored this over long time scales such as a decade. In general, those that used data sampling multiple provinces including both urban and rural areas in China reported the mean ranges from about 4% to 12%, and there is a trend that the PHI prevalence was moderately increasing since 2004 (Hou and Zhang, 2017, Jin et al., 2016, Yuan et al., 2014, Liu and Wang, 2012). Additionally, many studies refer to the total PHI premium income, a measurement in state administrative statistics, which was gradually increasing through the 2000s in absolute terms (China Insurance Regulatory Commission, 2014) (also see Figure 1.2).

It is worth noting that rather than describing these statistics above, these related studies paid most attention to the determinants of PHI prevalence and their model adjusted effects, which are elaborated as follows.

Distribution

There is weak evidence that the prevalence of PHI is greater in affluent eastern provinces than in poorer inland provinces (see Table 2.1). The only explicit evidence is from the study that examined the 2006 CHNS data and showed that rural residents in eastern provinces were more associated with having PHI than their inland counterparts (Qu and Wang, 2010). But it could have given a more reliable result by analysing more waves of CHNS data. Other evidence is indirect. A study based on

2007-2013 administrative statistics showed that the income from PHI premiums per capita was greater in eastern provinces than in central or west inland provinces (Wang et al., 2015). In addition to the two above, a different analysis based on the 2004-2013 administrative data showed that the development of the PHI market, indicated by an index derived from PHI income per GDP, PHI income per capita, and market concentration, was more positively correlated with healthcare resources, indicated by an index derived from densities of healthcare facilities, personnel and beds, in eastern provinces than inland provinces. The authors explained that this means that as healthcare resources became richer during this period, the PHI market developed faster in the east than the inland of China (Suo et al., 2015).

There is weak evidence for a greater prevalence of PHI in urban areas than rural areas, too (see Table 2.1). One study demonstrated that urban registrants were more associated with PHI coverage than rural registrants based on the 2011 CHALRS data (Yue and Zou, 2014). Analysing the 2011 and 2013 data from the same dataset, another likewise reported that rural registered were less associated with coverage of PHI or both SHI and PHI than their urban counterparts (Jin et al., 2016). Another study, however, based on the 2012 data of a telephone survey in the three eastern cities of Beijing, Shanghai, and Xiamen (Fang et al., 2012), reported no significant difference. As well as these, one study that separately investigated the effects of urban SHI schemes and the rural NCMS, based on the 2000, 2004 and 2006 data from the CHNS (Liu and Wang, 2012) showed that in urban areas students were more associated with having PHI than non-students, while in rural areas this effect disappeared, possibly because commercial insurers offered urban schools group insurance but did not offer it in rural areas.

However, it is noted that three of the four studies mentioned in the above paragraph used official registrations rather than actual residences to indicate urban/rural differences, therefore weakening the evidence. This is because the registrations are highly correlated with but are not necessarily equal to actual residences due to migration without change in *hukou* registration (the official residency registration system in China). *Hukou* status is often associated with entitlements to local benefits, and hence changing hukou registration is often be difficult (for detail see Section 3.2.2).

The evidence for a greater prevalence of PHI among immigrants than locals in urban areas seems stronger than the two above, triangulated by three studies looking at longitudinal nationwide data and cross-sectional data from a southern city and a northern city, respectively (see Table 2.1). One study based on the 2011 and 2013 data of the CHARLS, showed that immigrants were either more associated with being insured by PHI, or completely uninsured, than locals (Jin et al., 2016). Based on data from the 2010 questionnaire survey in Shenzhen, an affluent coastal city, another study also found that immigrants without local official residency registration (*hukou*) were more associated with being insured by PHI and less associated with being insured by SHI than local registrants (Lam and Johnston, 2012). Under the incentive of income tax breaks, immigrants were less willing to buy PHI than local residents, as was shown by a study based on the 2010 data from Tianjin, a northern coastal provincial municipality (Zhu and Yu, 2015). This is possibly because immigrants tend to work in informal sectors with lower income and thus would be less likely than locals to meet conditions for tax breaks.

Finally, a few studies found a greater prevalence of PHI among those working in the private, informal sector than public, formal sector employees (see Table 2.1). A study on the willingness to buy PHI based on household survey data from four provinces, showed that employees in the private sector or the self-employed were more willing to buy complementary PHI, relative to employees in government or state-run institutions (Ying et al., 2007). Another study, using the 2012-2013 data from a survey in five cities of five provinces, found that those working in the informal sector was associated with being covered by PHI relative to those working in the formal sector (Dong and Zhao, 2013). One study mentioned above also found that government officials were less willing to buy PHI than others (Zhu and Yu, 2015). However, the evidence is compromised, because the indicators in two of the three studies are willingness to buy instead of real enrolment.

It is worth considering the unequal prevalence of PHI in the context of inequalities in SHI coverage. SHI schemes in affluent eastern provinces are generally more generous in benefit coverage and compensation than those in the less-affluent inland areas (Meng et al., 2012, Suo et al., 2015, Liang and Langenbrunner, 2013). Rural residents are more likely than their urban counterparts to face financial and other barriers to access when they need healthcare, the provision of which is disproportionately concentrated in cities (Liang and Langenbrunner, 2013). Rural-to-urban migrants may find that their SHI coverage does not provide access to an adequate package of benefits in the cities (Cheng et al., 2014, Zhao et al., 2011, Qin et al., 2014, Zhao et al., 2014). Coverage under the government FMS is more generous than the UEBMI for employees in formal sectors, which are in turn more generous than other SHI schemes (Liang and Langenbrunner, 2013, Yip and Hsiao, 2009a). In theory, for groups disadvantaged by limited SHI coverage, greater prevalence of PHI among them than among the advantaged groups would help to reduce the inequalities related to SHI coverage, otherwise increase the inequalities.

Table 2.1 Unequal distributions of PHI prevalence

Comparison	*Ref. ID*	*Greater prevalence associated with*	*Indicator*
East residents vs. inland residents	(Wang et al., 2015)	East	PHI income
	(Qu and Wang, 2010)	East	Rural enrolment
	(Suo et al., 2015)	East	Correlation between PHI development and health resources
Urban residents vs. rural residents	(Yue and Zou, 2014)	Urban	Enrolment
	(Jin et al., 2016)	Urban	Enrolment
	(Fang et al., 2012)	Neutral	Enrolment
	(Liu and Wang, 2012)	Urban	Student enrolment

Migrants vs. locals	(Jin et al., 2016)	Migrants	Enrolment
	(Lam and Johnston, 2012)	Migrants	Enrolment
	(Zhu and Yu, 2015)*	Locals	Willingness to buy
Private, informal employees vs. public, formal employees	(Ying et al., 2007)	Informal employees	Willingness to buy
	(Dong and Zhao, 2013)	Informal employees	Enrolment
	(Zhu and Yu, 2015)	Non-government employees	Willingness to buy
* Under the incentive of income tax breaks All comparisons passed the significance test, otherwise neutral was reported.			

Interactions between PHI and SHI

Some studies focused on the correlation of PHI premium income with SHI coverage (with different indicators) (see Table 2.2). Although these studies examined a range of different regions, time periods and SHI schemes, and vary in quality in terms of methods that they used, all of them led to the conclusion that PHI premium income had a positive correlation with SHI expansion, which was indicated by such diverse indicators as covered population, funding, and compensation (Li, 2009, Wang, 2009, Wang, 2011, Zhu and Gui, 2014, Wang et al., 2015, Zheng and Hua, 2013, Lv, 2013). Overall, this seems to be very strong evidence.

Specifically, five studies applied regression models to control for background factors such as average age, gender, affluence and education. One examined the correlation between the percentage of enrolment in all SHI schemes and PHI income using the 2007-2013 data from 31 provinces (all provincial regions in China except Hong Kong, Macao and Taiwan) (Wang et al., 2015), while another one carried out a similar analysis but using the 2002-2007 data from three provincial regions (Beijing, Shanghai, and Hubei) (Li, 2009). Three studies focused on urban SHI schemes. One examined the impact on PHI income from the fund income of two urban SHI schemes, i.e. the UEBMI and the URBMI[14], using the 2000-2007 data from 31 provinces (Wang,

[14] UEBMI and URBMI refer to the Urban Employees' Basic Medical Insurance and the Urban Residents' Basic Medical Insurance, respectively.

2009). One used the same indicator but only examined the UEBMI with the 2002-2009 data from 30 provinces (Wang, 2011). Another focused on both the UEBMI and the URBMI, but used the average compensation from SHI as the indicator of SHI coverage, based on the 2003-2012 provincial data from 30 provinces (Zhu and Gui, 2014).

Among the five regression studies above, three used fixed effects models (with or without an instrumental variable) or dynamic models to deal with panel data (Wang et al., 2015, Wang, 2011, Zhu and Gui, 2014). The remaining two are less valid methodologically, because they only used linear models on pooled data (Li, 2009, Wang, 2009), failing to take advantage of the longitudinal data structure, and are thus more vulnerable to endogeneity problems. However, because of the consistency of findings across methodologies, the variation in quality does not compromise the strength of the evidence.

The two studies that did not use regression models also reached the same conclusion. The first used a measurement model in a composite system to calculate the degree of coordination between total SHI fund income and PHI income, and found that it was fair or excellent in most of 31 provinces from 2005 to 2010 (Zheng and Hua, 2013). The second introduced the 'coupling theory' to investigate collaborative development levels between PHI and the rural SHI scheme, NCMS[15], based on 2005-2011 national statistics (Lv, 2013). There was a coupling relationship with moderate strength between the PHI market (indicated by income, expenditure, claim ratio, etc.) and the NCMS development (indicated by income, expenditure, ratio of income and expenditure, etc.), suggesting that NCMS and PHI coverage were mutually reinforcing.

[15] NCMS refers to the New Cooperative Medical Scheme.

Table 2.2 The aggregate-level relationship between PHI and SHI						
Ref. ID	*PHI indicator*	*SHI indicator*	*Correlation*	*SHI schemes*	*Period*	*Area*
(Wang et al., 2015)	Income	Percentage of enrolees	Positive	All	2007-2013	31 provinces
(Li, 2009)	Income	Population of enrolees	Positive	All	2002-2007	3 provinces
(Wang, 2009)	Income	Fund income	Positive	UEBMI & URBMI	2000-2007	31 provinces
(Wang, 2011)	Income	Fund income	Positive	UEBMI	2002-2009	30 provinces
(Zhu and Gui, 2014)	Income	Average compensation	Positive	UEBMI & URBMI	2003-2012	30 provinces
(Zheng and Hua, 2013)	Income	Fund income	Positive	All	2005-2010	31 provinces
(Lv, 2013)	Compound index *	Compound index †	Positive	NCMS	2005-2011	Nationwide ‡

* index generated by income, expenditure, claim ratio, etc; † index generated by income, expenditure, ratio of income and expenditure, etc.; ‡ the national statistics were used without reporting the number of provinces.
UEBMI = Urban Employees' Basic Medical Insurance; URBMI = Urban Residents' Basic Medical Insurance; NCMS = New Cooperative Medical Scheme.
All presented positive or negative correlations passed the significance test, otherwise neutral correlation was reported.

PHI's total premium income is determined by enrolment and the price; and studies of premium income do not disaggregate these two determinants (Li, 2009, Wang et al., 2015). The positive association between SHI coverage and PHI premium income is possibly because SHI increases healthcare prices and thus PHI premium prices, rather than PHI prevalence. Some studies examined individual-level enrolment into PHI to focus on prevalence directly. Unlike the studies of premium income data, these studies paint a mixed picture in terms of the relationship between SHI coverage and the enrolment into PHI. In general, the number of reviewed studies that support the positive impact of SHI coverage on PHI enrolment (Liu and Wang, 2012, Qu and Wang, 2010, Zhu and Yu, 2015, Zhu and Wang, 2016) slightly exceeds those that show the opposite effect (Yuan et al., 2014, Liu et al., 2014, Jin et al., 2016), in addition to one study that reported a neutral (insignificant) impact (Hou and Zhang, 2017), but the overall effect is ambiguous (see Table 2.3).

For more details, among these studies above, those based on data collected between 2000 and 2010 tended to report a positive relationship between PHI and SHI, regardless of the particular scheme (see Table 2.3). They included one previously mentioned study based on the 2000, 2004, and 2006 data from the CHNS (Liu and Wang, 2012); one that analysed the NCMS using the 2006 CHNS data (Qu and Wang, 2010); and one that also focused on the NCMS by comparing the 2006 and 2009 CHNS data (Xu et al., 2013). In addition, the study that used the willingness to buy PHI rather than the real enrolment[16] based on the 2010 data from Tianjin also found a positive correlation (Zhu and Yu, 2015). Another study using the same dataset led to the same conclusion (Zhu and Wang, 2016). In sum, they all used methodologically justifiable regression techniques (see Appendix A), but the latter two are less reliable in drawing a relationship between PHI enrolment and SHI coverage because they used willingness to buy rather than real enrolment as the indicator.

The negative impact was reported mainly by studies examining later data, or those taking into account very early data (see Table 2.3). For example, the study based on the 2011 and 2013 data of the CHARLS, reported that enrolment into SHI, including the NCMS, the URBMI and the UEBMI, was negatively associated with enrolment into PHI based on the whole population. However, after disaggregation the negative correlation was only significant in urban areas (Jin et al., 2016). Additionally, a retrospective study, which employed the Chi-square test based on the 2010-2013 data of 681 myocardial infarction patients in Shanghai, a provincial municipality, found that the non-SHI group had a significantly higher percentage of PHI coverage than

[16] Enrolment theoretically depends on a combination of willingness to buy and capacity to buy. Using only willingness to buy weakens the evidence for enrolment.

SHI groups (Liu et al., 2014). However, this finding is less convincing because this study did not try to match individual characteristics among the compared groups. On top of these two, another study looking at a long span of CHNS data, from 1989 to 2009, reported that public insurance programmes had a negative association with PHI enrolment (Yuan et al., 2014). The study comparing the 2004 and 2006 CHNS data, demonstrated that enrolment into NCMS had a negative association with PHI enrolment (Xu et al., 2013).

Other studies suggested that the association varied among different groups (Table 2.3). One found that the NCMS membership was positively associated with adult PHI enrolment but negatively associated with children's, especially in lower income groups, based on the 2000, 2004, and 2006 CHNS data (Liu et al., 2011b). Using the 2006 data from Shanghai, one study found that in the low-income group and middle-high-income group, SHI (as a whole) enrolment was negatively associated with PHI enrolment, while in the low-middle-income group, the correlation became positive (Xu, 2007).

Table 2.3 The individual-level relationship between PHI and SHI

Ref. ID	*Population*	*Correlation*	*SHI schemes*	*Period*	*Area*
(Liu and Wang, 2012)	Urban	Positive	Urban schemes	2000-2006	9 provinces
(Liu et al., 2011b)	Adult	Positive	NCMS	2000-2006	9 provinces
	Child	Negative			
(Xu et al., 2013)	Rural	Negative	NCMS	2004-2006	9 provinces
		Positive		2006-2009	
(Qu and Wang, 2010)	Rural	Positive	NCMS	2006	9 provinces
(Xu, 2007)	Low income/middle-high income	Negative	All	2006	Shanghai
	Low-middle income	Positive			
(Yuan et al., 2014)	Mixed	Negative	All	1989-2009	9 provinces
(Zhu and Yu, 2015)	Mixed	Positive	All	2010	Tianjin
(Zhu and Wang, 2016)	Mixed	Positive	All	2010	Tianjin

(Jin et al., 2016)	Mixed	Negative	All	2011-2013	28 provinces
	Urban	Negative			
	Rural	Neutral			
(Liu et al., 2014)	Mixed	Negative	All	2010-2013	Shanghai
(Hou and Zhang, 2017)	Urban	Neutral	URBMI	2004-2011	9 provinces
UEBMI = Urban Employees' Basic Medical Insurance; URBMI = Urban Residents' Basic Medical Insurance; NCMS = New Cooperative Medical Scheme. All usually include government officials' FMS. All presented positive or negative correlations passed the significance test, otherwise neutral correlation was reported.					

2.2.3 Effects on access

Impact on generic utilisation

In the literature, access to healthcare is mainly indicated by utilisation. Generic utilisation is a common indicator; that is, using healthcare during a certain period, regardless of the kind of healthcare utilised. The reviewed studies that used this indicator report mixed results (Table 2.4). Specifically, a study based on the 2004 CHNS data, which particularly focused on those who had reported being ill in the last four week period (You and Kobayashi, 2011), and a study based on the 2000, 2004, 2006, and 2009 CHNS data (Jiao, 2015), both reported that PHI had an insignificant association with utilisation. Contrarily, a study using the 2008 two-province CHARLS data, reported that having PHI is more associated with utilisation compared to not having PHI (Chai, 2013). The same author, based on the same data, reported that having PHI is more associated with utilisation compared to the NCMS (Chai, 2014). However, a study looking at the data collected in 2010 in Shenzhen, found insignificant effects (Lam and Johnston, 2012).

Critically, it is worth noting that some of the above studies may be methodologically questionable. To estimate the effect of having PHI for the general population, only modelling the reporters of illness may be problematic in generalisation of the finding, considering classic sample selection bias (Heckman, 1979). Furthermore, referring to NCMS members rather than those without PHI may be also problematic, since this has in effect ruled out the possibility that individuals are covered by both PHI and NCMS.

Impact on utilisation of inpatient care

Two studies that specially investigated the effect of PHI on the utilisation of inpatient care demonstrated a positive correlation (see Table 2.4). Among them, one study based on the 2007 and 2008 data of State Council URBMI Household Survey (Zang et al., 2012) and one based on the 2014 data of a household survey in three cities in Sichuan province, a populous southwest province (Li et al., 2016), reported that enrolment of PHI had a positive relationship with the probability of using inpatient care in the last year. Another study, based on the CHNS data from 2000, 2004, 2006 and 2009, reported that the enrolment of PHI was associated with increasing lengths of hospitalisation between 2000 and 2004, but such an association was not significant between 2006 and 2009 (Jiao, 2015). Only one study that focused on rural-to-urban migrants using 2007-2010 URBMI survey data reported PHI as having no effect on inpatient utilisation (Qin et al., 2014).

However, from the aggregate perspective, no significant relationship was reported. A study that analysed administrative statistics found an insignificant relationship between the regional depth of PHI coverage – the total premium income of PHI insurers over GDP in the province – and the average length of hospitalisation (Wang, 2012). Another aggregate-level study using county-level data also found an insignificant relationship between the percentage of PHI enrolees in a rural county and the number of inpatient visits per 1000 in the last 52 weeks (about a year) (Chau, 2010).

Overall, all these studies used methodologically justifiable regression models (see Appendix A). Interestingly, those based on data of wider scope tend to report an insignificant or mixed result (Qin et al., 2014, Wang, 2012, Chau, 2010, Jiao, 2015). It is also noted that the indicators of inpatient utilisation are not identical. In addition to the different levels of measurements, the length of hospitalisation represents the intensity of utilisation more than the frequency of utilisation, as other measures in effect imply. This may be another reason for the mixed outcomes.

Impact on utilisation of outpatient care

There is modest evidence that at the individual level there was no significant positive relationship between PHI enrolment and using outpatient care in a certain period (usually four weeks prior to the survey) (Table 2.4). The evidence is supported by the study using the 2004, 2006 and 2009 CHNS data (Yang, 2013), the study using the 2007-2010 data of the State Council URBMI Household Survey (focusing on rural-to-urban migrants) (Qin et al., 2014), the study using the 2007 and 2008 data of the State Council URBMI Household Survey (Zang et al., 2012), the study focusing on school pupils in a district of Beijing (Zhu et al., 2008), and the study focusing on the utilisation of community health services in Dongguan, a southern city (Yao et al., 2012). The simple possible explanation of these consistent outcomes is that most PHI plans do not reimburse payments for outpatient care to any great extent (Ng et al., 2012). However, the quality of the findings from the latter two is relatively low, because they are only derived from the Chi-square tests without controlling individual characteristics.

In contrast, only one individual-level study, using the 2011 and 2013 CHARLS data, reported a positive relationship between PHI enrolment and use of outpatient care (Wang et al., 2016). However, in this study, the PHI was restricted to working as substitutive health insurance, in other words an alternative to a SHI scheme. The authors also examined the effect of complementary health insurance on outpatient utilisation, but found no significant correlation.

The only reviewed aggregate-level study that analysed the 2003 NHSS county-level data reported that the percentage of PHI enrolees in a rural county had a positive relationship with the number of outpatient visits per 1000 population during a two week period (Chau, 2010). Its difference from the individual-level outcomes may result from the different measures of utilisation. Like premium income, visit frequency can be influenced by extreme values. In this sense, it not only reflects the probability of each utilisation but also their intensity. In addition, counties may have considerable endogenous factors that influence both outpatient visits and PHI enrolments. Longitudinal modelling can solve this problem, but it was not applied in this aggregate study.

Impact on utilisation of preventative care

In China few PHI policies cover preventative care (EY, 2016b), which usually refers to health services for the generally healthy who are aiming to prevent illness, mainly through vaccinations and physical examination. Unexpectedly, all three related studies reported that PHI enrolment had a significantly positive relationship with the probability of using preventative services (see Table 2.4). These studies are: the one with the 2004, 2006 and 2009 CHNS data (Yang, 2013), one with the 2007-2010 data of the State Council URBMI Household Survey focusing on rural-to-urban migrants (Qin et al., 2014), and one examining the CHNS data from 2000, 2004, 2006 and 2009 (Jiao, 2015). One possible explanation for this positive relationship is that enrolment into PHI sometimes requires a physical examination, since insurers try to prevent themselves from adverse selection. Another factor is the association between buying PHI and concern with self-health, increasing the use of preventative services.

The dual insurance effects

Three reviewed studies investigated the effect of dual insurance (i.e. of both SHI and PHI), reporting mixed outcomes (see Table 2.4). Two were focused in the individual level. One looking at data from Shenzhen (Lam and Johnston, 2012), and another using the 2008 two-province CHARLS data, both reported that dual insurance of SHI and PHI did not have an additional effect on the generic utilisation of healthcare (Chai, 2013). Unlike the individual-level evidence, the study of the 2006-2010 administrative statistics showed a positive interactive effect on the average length of hospitalisation between the depth of PHI (premium income over GDP) and the coverage of urban SHI (the percentage of regional SHI enrolees), suggesting an additional effect of dual insurance on inpatient utilisation (Wang, 2012). However, it is noted again that PHI premium income does not directly represent its coverage prevalence.

Unequal impacts on access

Three studies examined unequal access to healthcare across the population associated with PHI, but they focused on different aspects, not mutually supported (see Table 2.4). The study on the 2008 two-province CHARLS data also modelled urban data and rural data separately, in addition to models of the whole population (Chai, 2013). For the urban population, the positive associations of SHI and PHI with generic utilisation were significant and mutually-reinforcing, while for the rural population, all effects were insignificant. This suggests that SHI and PHI as well as dual insurance, performed better at promoting utilisation in urban areas than in rural areas. Another study found higher income earners were more associated with having PHI and using preventative health services than lower income earners (Yang, 2013). Nonetheless, as previously stated, the increased use of preventative care may not relate to PHI directly. The third study using the 2010 Shenzhen data compared the associations of SHI, PHI and dual insurance with the generic utilisation of healthcare between migrants and local registrants (through the *hukou* system). However, it did not find any significant differences (Lam and Johnston, 2012).

Table 2.4 The correlation between PHI and access to healthcare					
Ref. ID	*Area*	*Period*	*About*	*Level*	*Results*
(You and Kobayashi, 2011)	9 provinces	2004	Generic utilisation	Individual	No correlation
(Chai, 2014)	2 provinces	2008	Generic utilisation	Individual	Positive (referring to the NCMS)
(Chai, 2013)	2 provinces	2008	Generic utilisation	Individual	Positive for the whole and urban areas; no correlation in rural areas; the utilisation-promotion effect of PHI and SHI were accumulative only in urban areas
(Lam and Johnston, 2012)	Shenzhen city	2010	Generic utilisation	Individual	No correlation; no difference existed between migrants and local registrants
(Li et al., 2016)	3 cities in Sichuan province	2014	Inpatient utilisation	Individual	Positive
(Jiao, 2015)	9 provinces	2000, 2004 2006, 2009	Inpatient and preventative utilisation	Individual	Positive with the both utilisations (the positive correlation with inpatient utilisation only existed in 2000-2004)
(Zang et al., 2012)	9 cities in different provinces	2007, 2008	Inpatient and outpatient utilisation	Individual	Only positive with inpatient utilisation
(Wang, 2012)	31 provinces	2006-2010	Inpatient utilisation	Provincial	No correlation; SHI and PHI had an additional effect on utilisation
(Chau, 2010)	31 provinces	2003	Inpatient and outpatient utilisation	County	Only positive with outpatient utilisation
(Qin et al., 2014)	9 cities in different provinces (migrants only)	2007-2010	Inpatient, outpatient and preventative utilisation	Individual	Only positive with preventative utilisation

(Yang, 2013)	9 provinces (rural only)	2004, 2006, 2009	Outpatient and preventative utilisation	Individual	Negative with outpatient utilisation; positive with preventative utilisation; higher income earners were more likely to have PHI and use preventative care
(Zhu et al., 2008)	Pinggu county of Beijing (school pupils only)	2005	Outpatient utilisation	Individual	No correlation
(Yao et al., 2012)	Dongguan city	2011	Outpatient utilisation (community services)	Individual	Negative (referring to SHI schemes)
(Wang et al., 2016)	28 provinces	2011, 2013	Outpatient utilisation	Individual	Positive for PHI as primary health insurance only; no correlation for supplemental PHI
If unspecified, all comparisons are between enrolees and non-enrolees of PHI, utilisation is indicated by the probability of using a certain kind of healthcare, and presented non-neutral correlations passed the significance test.					

2.2.4 Financial protection

Preventing catastrophic health expenditure

The effect of PHI on the incidence of catastrophic health expenditure is unclear because the relevant studies give mixed results (see Table 2.5). The study based on the 2008 and 2013 Shaanxi NHSS data found that in both 2008 and 2013 an absence of PHI was correlated with the higher incidence of catastrophic health expenditure. The same relationship was found between the absence of SHI and catastrophic health expenditure as well (Xu et al., 2015). However, another study of data sampled from eight provinces in 2014 reported that there was no significant difference in the incidence of catastrophic health expenditure between PHI status (Wang and Wang, 2017). In addition to the mixed results, the first study only examined data from one province, and second one simply used Chi-square tests that did not control individual characteristics, compromising reliability and validity of the findings.

Impact on OOP payments for healthcare

Four studies looking at the relationship between PHI and OOP payments for healthcare found little evidence that PHI reduced OOP payments (see Table 2.5). Among them, one based on the 2004 CHNS data reported that PHI had no significant association with OOP payments (You and Kobayashi, 2011). Another study using the 2011-2012 CLHLS data found the same (Zeng et al., 2017). A study using the 2000, 2004, 2006 and 2009 CHNS data even found that PHI was associated with increased OOP payments as a share of total expenditure on treatment in 2000-2004, but had no effect in 2006-2009 (Jiao, 2015). Likewise, the study analysing survey data sampled from three eastern cities (Beijing, Shanghai and Xiamen) in 2011 reported that PHI was correlated with the higher probabilities of OOP payments of over ¥1000 and over ¥5000, respectively (¥1≈ £0.11 or \$0.14) (Fang et al., 2012). It is interesting that the second study found that using PHI as the main health financing method was associated with reduced OOP payments (Zeng et al., 2017), implying that it was complementary PHI (as the secondary financing method) that failed to reduce OOP payments.

However, some of these studies seem problematic in modelling (OOP) health expenditure (and these on total health expenditure in the following section likewise), such as using linear regression (Jiao, 2015, Zeng et al., 2017), which is not suitable for heavily-skewed data with most of observations being zero due to inclination of violation of error normality (Wooldridge, 2015: 47, Wooldridge, 2002: 560-566), or only including the selected population (those who were self-reported ill or injured) (You and Kobayashi, 2011), so as to compromise generalisability of the findings. The one that transformed the OOP payments into binary variables (Fang et al., 2012) avoid such problems, but at the expenses of losing information.

Impact on total healthcare expenditure

All four related studies reported that PHI was associated with increased total individual expenditure on healthcare – gross payments before insurance reimbursement (see Table 2.5). These studies are: one analysing patients' data from an affiliated hospital of Peking University collected in 2003 (Wang et al., 2010); the aforementioned one examining three-city data (Fang et al., 2012); the one using the 2008 two-province CHARLS data (Chai, 2013), and the one using the 1989-2009 CHNS data (Yuan et al., 2014). This is not surprising, because PHI members tended to use healthcare more intensively, and hence incur higher total individual health expenditure, as the theory indicates in Section 1.3 (Pauly, 1968, De Meza, 1983).

It is worth noting that rising total healthcare expenditure does not necessarily increase financial risk, since it can be reimbursed by health insurance. Rather, it could indirectly indicate the enhanced individual utilisation of healthcare (Chai, 2013, Wang et al., 2010). However, at the aggregate level, increased total expenditure on healthcare has other implications. On the one hand, it signifies an increasing average cost of healthcare, warning the commercial insurers of moral hazard (Yuan et al., 2014). On the other hand, this suggests that PHI may intensify the financial burden of the health system, thus concerning the government (Fang et al., 2012).

At the aggregate level, one, which analysed the 2003 NHSS county data, reported that the percentage of PHI coverage in the county had no significant correlation with the per-capita annual medical expenditure of this region (Chau, 2010) (see Table 2.5). The other, which investigated administrative statistics from 2006 to 2012, found that per-capita PHI premium spending had a significant relationship with lower per-capita medical expenditure at the provincial level (Cui et al., 2016). The former study's indicator of PHI is more relevant to the sense of insurance coverage than the latter's, as previously discussed (Wang, 2011, Li, 2009).

Inequity in financing of PHI

Most reviewed studies on the vertical equity of PHI financing used the Kakwani index to evaluate its financing distribution across income quintiles (see Table 2.5). Specifically, a study based on the rural NHSS data of Xinjiang, a northwest border province, reported that PHI financing was progressive (i.e. those with higher incomes contributed disproportionately more) in 2003 and 2008 (Li et al., 2012c). Another study researching the 2010 survey data in an independent administrative region in Xinjiang reported that PHI had little impact on financial redistribution (Liu et al., 2013). Two studies examined data from Gansu, a northwest province, and Heilongjiang, a northeast province, respectively. In Gansu, PHI was slightly progressive in both urban and rural areas in 2002 and 2007 (Chen et al., 2012); in Heilongjiang, PHI in urban areas was regressive (the poorer contributed more) in 2002 but became progressive in 2007, while PHI in rural areas was progressive in 2002 but became regressive in 2007 (Chen et al., 2014).

All of the above outcomes are insignificant, however. Additionally, unlike SHI or general taxes, PHI only covers a small number of people, so the outcomes of studies based on the Kakwani index are not informative about its impact on equity from the perspective of the whole healthcare financing system. Except for these above, the study on the 2000-2009 CHNS data found that between 2000 and 2004 PHI significantly increased the share of OOP health payment for treatment in the high-income group but not in the low-income group. However, the study did not report that whether it was just because the former used more services and medicines than the latter (Jiao, 2015).

Table 2.5 The correlation between PHI and financial risk

Ref. ID	*Area*	*Period*	*About*	*Level*	*Results*
(Xu et al., 2015)	31 provinces	2008, 2013	Catastrophic health expenditure	Individual	Negative
(Wang and Wang, 2017)	8 provinces	2014	Catastrophic health expenditure	Individual	No correlation
(You and Kobayashi, 2011)	9 provinces	2004	OOP payments	Individual	No correlation
(Zeng et al., 2017)	22 provinces	2011-2012	OOP payments	Individual	Negative for PHI as the main payment method; otherwise no correlation
(Jiao, 2015)	9 provinces	2000, 2004, 2006, 2009	OOP payments (as a share of total expenditure for treatment)	Individual	Positive only between 2000 and 2004, and only for the high-income group, but not for the low-income group
(Fang et al., 2012)	Three eastern cities	2011	OOP payments and total health expenditure	Individual	Positive with the probabilities of the OOP payments over ¥1000 and over ¥5000, respectively, and total health expenditure over ¥1000
(Wang et al., 2010)	An urban teaching hospital; 101 villages	Urban: 2003; Rural: 2005	Total health expenditure	Individual	Positive (comparing to regular insurance, an outdated insurance with limited coverage of medicine and services)
(Chai, 2013)	2 provinces	2008	Total health expenditure	Individual	Positive
(Yuan et al., 2014)	9 provinces	1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009	Total health expenditure	Individual	Positive
(Chau, 2010)	31 provinces	2003	Per-capita health expenditure	County	No correlation (the indicator of PHI is percentage of PHI enrolees)

(Cui et al., 2016)	31 provinces	2006-2012	Per-capita health expenditure	Provincial	Negative (the indicator of PHI is per-capita PHI premium spending)
(Li et al., 2012c)	Rural Xinjiang province	2003, 2008	Financial inequity	Individual	Progressive*
(Liu et al., 2013)	The Corps in Xinjiang province	2010	Financial inequity	Individual	Little redistributive effect
(Chen et al., 2012)	Gansu province	2002, 2007	Financial inequity	Individual	Progressive for both urban and rural areas*
(Chen et al., 2014)	Heilongjiang province	2002, 2007	Financial inequity	Individual	In 2002, regressive in cities and progressive in villages; in 2007, progressive in cities and regressive in villages*
If unspecified, all comparisons are between enrolees and non-enrolees of PHI and presented non-neutral correlations passed the significance test. *The Kakwani index was not significant. Progressive means Kakwani index > 0; Regressive means Kakwani index < 0.					

2.3 Discussion

2.3.1 Summary and discussion

In China, descriptive statistics show that the overall prevalence of PHI moderately increased over time since the early 2000s. However, weak evidence hints that the distribution of PHI may be unequal. Spatially, those living in the more affluent east provinces and urban areas appear to be more associated with PHI coverage than those living in laggard inland provinces and rural areas. Additionally, urban immigrants appear to be more associated with PHI coverage than urban locals, and those working in the private sector or individual business appear to be associated with PHI coverage than employees of public, formal sectors, possibly because the former have poorer access to SHI coverage than the latter (Liang and Langenbrunner, 2013, Yip and Hsiao, 2009a) and thus more need PHI to complement. Most related studies focused on the impact of SHI. There is strong evidence that as SHI expands, PHI premium income also increases, controlling for economic growth and population characteristics. In contrast, the relationship between individual SHI enrolment and PHI enrolment is ambiguous. Weak evidence suggests that this relationship may vary among different populations, especially changing over time, with a negative relationship found in more studies focusing on a more recent period.

In terms of access to healthcare, the evidence about the relationship between PHI enrolment and the generic utilisation of healthcare is mixed. For the utilisation of specific types of care, there is weak evidence for a positive correlation between PHI enrolment and the utilisation of inpatient care, and modest evidence for a neutral correlation between PHI enrolment and the utilisation of outpatient care. The compensation policies of the majority of PHI products which focus on critical illnesses and inpatient care may explain this difference (EY, 2016b). Additionally, the reviewed studies show a positive correlation between PHI enrolment and the utilisation of preventative services, though little information shows that mainstream PHI products include such benefits. This may correlate with some PHI providers' preference for those who take advantage of preventative services, or higher levels of motivation among PHI buyers to look after their health. Few studies paid attention to unequal impact of PHI on access. Among them one suggests that PHI as well as the dual insurance of PHI and SHI appear more likely to increase utilisation in urban areas than in rural areas.

Financially, the OOP payment for healthcare, which deducts insurance compensation from the gross payment, is a popular indicator of individual financial risk, but there is little evidence to show that PHI impacts OOP payments for healthcare. There is also insufficient evidence to support a relationship between PHI and the incidence of catastrophic health expenditure, another indicator of financial risk taking both OOP payments and the living standard into account. Instead, PHI enrolment is convincingly associated with an increased individual total expenditure on healthcare, the gross payments for the utilisation of healthcare before insurance compensation. However, this correlates more with the financial burden of the system and the moral hazard that concerns governments and insurers, than direct financial risk to the healthcare users, because the expenditure may be substantially reimbursed by insurance. Additionally, no conclusion on PHI's impact on inequity in terms of the healthcare financing overall can be drawn from this review, because the reviewed studies on this issue are limited in their scope, and their outcomes are mostly insignificant.

2.3.2 Conclusion

The literature review concludes that as PHI prevalence and total premium income are gradually increasing since the early 2000s, there is weak evidence that the distribution of PHI is unequal in favour of eastern and urban residents, urban immigrants and private, informal sector employees, compared to their counterparts. As the key element of health reforms, SHI has an unclear impact on PHI take-up, possibly changing over time, due to conflicting evidence, although overwhelming evidence shows that the scaling-up of SHI has boosted total PHI premium income. The evidence about the effect PHI on the generic utilisation of healthcare is mixed, while fairly consistent evidence supports that PHI enrolment increases the utilisation of inpatient care but has little impact on the utilisation of outpatient care. There is little evidence for the correlation of PHI with reduction in OOP payments for healthcare or the falling risk of catastrophic health expenditure, while sufficient evidence shows that PHI enrolment increases gross expenditure on healthcare. Finally, inequalities in the effects of PHI and interaction of dual-insurance on access and financial protection are under-researched.

2.3.3 Research gaps in the literature

The unequal distribution of PHI is a potential source of health inequity, because PHI is likely to influence health resource allocation in favour of its enrolees rather than those in need (Kutzin et al., 2016). It has been well-documented that PHI has a socioeconomically unequal distribution under *laissez-faire* regulations, due to its voluntary enrolment dependent on economic demand, risk-related pricing and information asymmetry (Sekhri and Savedoff, 2006, Pauly et al., 2012). In addition to having a relatively deregulated PHI market, China is a country with notable regional disparities in economy and development (Liu, 2005, Liu et al., 2003, Shi et al., 2010), which may intensify the unequal distribution of PHI, because in theory PHI sellers may be concentrated in affluent areas and absent from remote, economically backward areas, where more socioeconomically disadvantaged people reside (Zweifel et al., 2007: 94). The literature only gives a hint with weak evidence that people living in more affluent east, urban areas may be more likely to be enrolled into PHI than those living in inland, rural areas, controlling for their individual characteristics. A multilevel analysis taking both individual-level variables and aggregate-level variables to explore the distribution of PHI would help to address this gap in empirical evidence.

Furthermore, whether PHI prevalence is enhanced or undermined by SHI expansion has been extensively debated internationally. According to a popular theory, the PHI market is decided by coverage of SHI due to the duplication of benefits, and thus SHI expansion crowds out PHI (Barros and Siciliani, 2012: 955-956). This may explain the higher prevalence of PHI among urban immigrants and private, informal sector employees than urban locals and public, formal sector employees, because the former are relatively poorly covered by SHI (Liang and Langenbrunner, 2013, Yip and Hsiao, 2009a). However, as SHI in China focuses on expanding coverage breadth (Yip et al., 2012), the government encourages PHI to complement SHI in depth and height, and hopefully thereby PHI enrolment and SHI enrolment can mutually reinforcing (Xiang, 2014). The evidence from this review is too mixed, but implies an over-time change in the relationship between SHI and PHI, plausibly echoing waves of health reform policies that steadily promoted the coverage of SHI in population and benefits (Yip et al., 2012, Meng et al., 2015). Accordingly, a study looking at data across a relatively long period would help to clarify the potential changes SHI could make on PHI.

In terms of the impacts of PHI on healthcare access and financial protection, there is moderate evidence that PHI facilitates the utilisation of inpatient care and thereby results in an increase of gross payments for healthcare, but after compensation this does not change financial risk caused by using healthcare. Apart from the effectiveness, equality is an important measure in appraisal of PHI's contribution to the progress towards UHC (Kutzin, 2013). Hopefully, the effects of PHI on utilisation and financial protection should be equal across different populations, whereas this is questionable in China, a large, spatially unequal country in economy and development. The literature review finds little evidence about inequities in health access or financial protection related to unequal impacts of PHI, because although a few studies tried to explore these questions, their data and results are insufficient, fragmented and inconsistent. For future research, as the WHO and the World Bank recommend, appropriate disaggregation of the population would be helpful to address the research gap (Boerma et al., 2014).

Another question is whether PHI has benefited its enrolees at the expense of others (Colombo, 2007: 230-231, Kutzin, 2013). To this end, the focus of examining a health insurance programme’s effect should be shifted from enrolees of the programme to the system in which the programme operates. In other words, it would be required to examine the contextual effect of the programme. Additionally, since the government advocates the complementary role of PHI in the SHI-dominated system (Xiang, 2014, Liu et al., 2011b), whether dual-insurance of SHI and PHI mutually reinforce or weaken in terms of facilitating healthcare access and financial protection concerns policy makers. However, the literature review finds very little evidence about the two questions.

On top of these, many previous studies on financial protection of PHI may be methodologically questionable. In a general population, a large part of health expenditure, regardless of whether it is OOP or gross, is commonly unobserved simply because there is no need and hence no utilisation. Under these conditions, linear models are vulnerable to violating the assumption of error normality (Wooldridge, 2015: 47, Wooldridge, 2002: 560-566), and hurdle models or count models that are immune from normality assumptions are superior (O'Donnell et al., 2008: 131-145, Min and Agresti, 2002). In this review, only two studies adopted hurdle models such as the Two-Part model and the Heckman selection model (You and Kobayashi, 2011, Chai, 2013), and one study transformed expenditure data into binary variables to circumvent this issue(Fang et al., 2012). Thus, the literature is in need of more related studies modelling health expenditure with more appropriate techniques.

Finally, no study systematically analysed all coverage dimensions of PHI and tried to associate them to the frame of UHC principles. These reviewed studies relied on more than ten data sources altogether, collected in various places, and in different time periods, and many of them only looked at a very limited period and examined one or two aspects about PHI, presenting a challenge to cross-reference.

In sum, the literature cannot produce a comprehensive understanding of PHI's role in China's UHC progress in terms of the three important dimensions, i.e. prevalence and distribution, access to healthcare, and financial protection, especially in respect of the inequities related to unequal distribution and unequal effects of PHI, and the relationship between PHI and SHI. It would be valuable to conduct a relevant investigation on the basis of consistent data with nationwide stratified sampling that cover a long enough period to reflect policy impacts, with methodologically proper analyses proceeding at both the individual and aggregate levels and disaggregation of the research population to examine inequalities.

Chapter Three: Concepts, Data and Variables

This chapter outlines the conceptual framework through which the study proceeds. The first three sections present the conceptualisation of the three outcome variables, and independent variables, drawing on the literature review. The following section relates to the rationale of the choice of dataset and basic information about the data source, the China Health and Nutrition Survey (CHNS). The last section presents the operationalisation of these concepts, related to the CHNS data, to generate variables for analyses. The following diagram shows the processes used to make the decisions resulting in the research design outlined in this chapter (Figure 3.1).

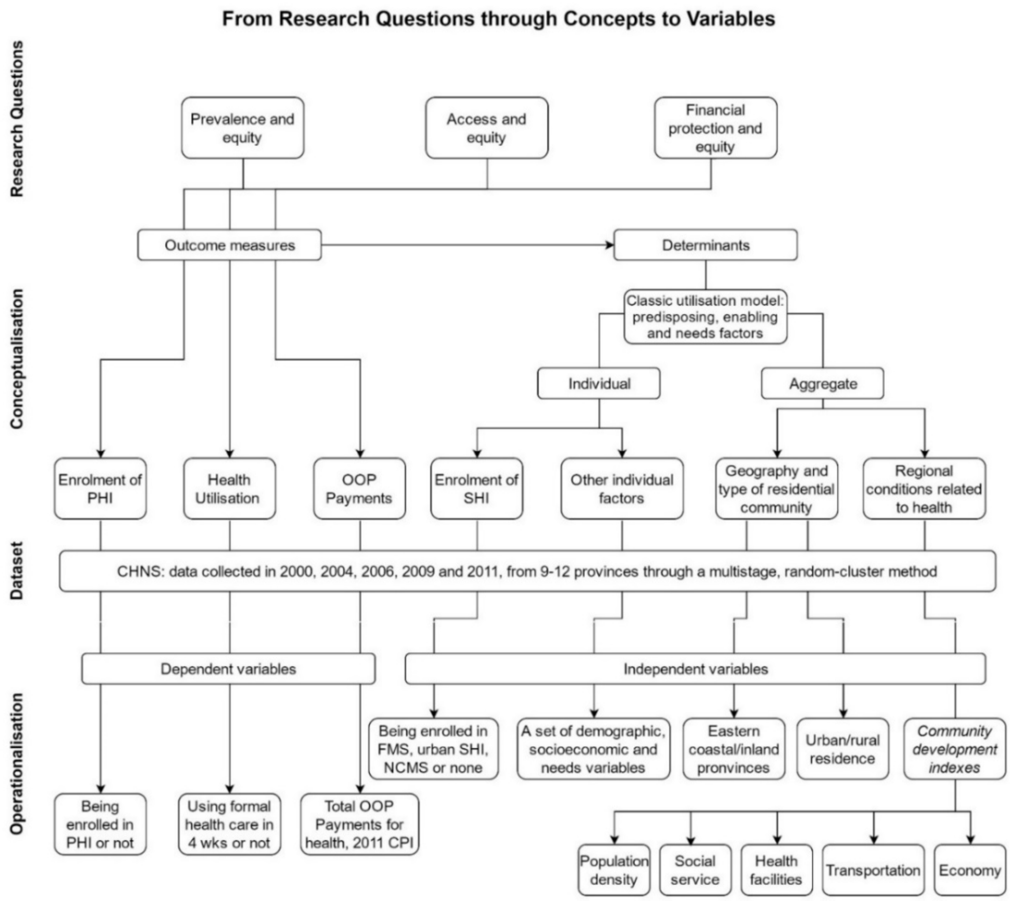

Figure 3.1: Flowchart of the conceptualisation and operationalisation in this chapter

3.1 Outcome measures

The theoretical literature suggests that coverage and benefits of voluntary private health insurance (PHI) may be limited in really existing markets. First, the demand for PHI is likely to have a socioeconomic gradient in even perfect markets; and in real markets, market failures linked to information asymmetries are likely to increase prices, further reducing demand for PHI, and supply of PHI may also be limited for some consumers (e.g. the chronically sick) (Arrow, 1963, Pauly, 1968, Cutler and Reber, 1998, Sekhri and Savedoff, 2006). Second, coverage of health insurance may increase additional utilisation beyond an optimal level, e.g. increasing expenditure on non-needed products and services (Pauly, 1968, De Meza, 1983), due to the problem of demand-side or supply-side moral hazard (Pauly, 1968). Third, the relationship of health insurance coverage and out-of-pocket (OOP) health expenditure is a complex one, e.g. if higher coverage drives increases in the demand for, and therefore the price of, healthcare (Pauly et al., 2009).

Relating to the research gaps identified by the literature review and the structured subsidiary research questions (Section 1.4.2), outcome measures that need to be conceptualised consist of 1) the proportion of the population that is covered under PHI, 2) the access that PHI has facilitated, and 3) the extent of financial protection that has been afforded by PHI.

3.1.1 The concept of prevalence

The concept of prevalence refers to the population that the scheme covers. In the preceding literature review, prevalence was commonly applied to indicate the demand for PHI by previous studies (Liu and Wang, 2012, Liu et al., 2011b, Xu et al., 2013, Qu and Wang, 2010, Xu, 2007, Yuan et al., 2014, Jin et al., 2016, Liu et al., 2014, Hou and Zhang, 2017), because of the relationship between demand and prevalence. Theoretically, demand refers to the combination of the willingness to purchase and the ability to pay (Morris et al., 2012: 8), resulting in actual enrolment. Unlike previous studies, this study directly uses prevalence rather than demand in its terminology, as the focus of interest is PHI's contribution to universal health coverage (UHC) objectives (prevalence of insurance coverage is one of them), rather than its market performance. This may be a more comprehensive perspective to study PHI.

Under this concept, whether the individual has been enrolled in PHI is a straightforward measure of prevalence at the individual level, which was widely adopted by the reviewed studies (Liu and Wang, 2012, Liu et al., 2011b, Xu et al., 2013, Qu and Wang, 2010, Xu, 2007, Yuan et al., 2014, Jin et al., 2016, Liu et al., 2014, Hou and Zhang, 2017). The aggregation of individual enrolment in a population forms the corresponding aggregative measure of prevalence, the percentage of enrolees in the population. However, in practice, due to the lack of such data in Chinese state statistics, on which these macro studies would rely, insurers' total income from PHI is often used instead (Liu and Wang, 2012, Liu et al., 2011b, Xu et al., 2013, Qu and Wang, 2010, Xu, 2007, Yuan et al., 2014, Jin et al., 2016, Liu et al., 2014, Hou and Zhang, 2017). The drawback to this is that income can be determined by not only the number of enrolees, but also the price of PHI and the average amount of products the enrolees buy, and therefore it does not exactly represent prevalence.

Focusing on PHI, this study needs to measure its prevalence at both the individual and aggregate levels. At the individual level, this concerns whether the individual has been enrolled in PHI (the most popular choice in the literature). At the aggregate level, the percentage of PHI enrolees (derived from the averages of individual data) would be selected. Especially, the two levels of measurements are compatible with the multilevel structure.

3.1.2 The concept of access to healthcare

According to the WHO, access refers to the opportunity or ability to obtain needed healthcare with financial protection (Evans et al., 2013). However, when measuring it, the concept of access is so complex that it has been conceptualised in several ways in the literature.

In the aforementioned literature, Aday and Andersen (1974) divided measures of access into process indicators, including characteristics of the health system and population, and outcome indicators, including utilisation and satisfaction. Later, Gulliford et al. (2002) continued to develop a four-dimension system of measuring access, in which service availability and utilisation of services were explicitly inherited from Aday and Andersen's model, while they added relevance and effectiveness, and equity as another two dimensions. Recently, Levesque et al. (2013) increased the number of measurable dimensions of access to five, including approachability, acceptability, availability and accommodation, affordability and appropriateness. Meanwhile, some WHO authors proposed three-dimensional access, including physical accessibility, financial affordability and acceptability (Evans et al., 2013).

Despite the conceptual complexity, the core relationship between the access and utilisation of healthcare has been long highlighted (Donabedian, 1972, Aday and Andersen, 1974). Penchansky and Thomas (1981) argued that the utilisation of healthcare – which means people in need of healthcare must overcome the personal, financial and organisational barriers to it – is the proof of access. In effect, utilisation, compared with the multi-dimensional measures, has been a practically popular indicator of access in the literature (Gulliford et al., 2002). For instance, though they suggest the five-dimension system, Levesque et al. (2013: 5), in reviewing past literature, admitted that "for some, under the broad domain, the study of access relates to similar aspects as the study of utilisation", and variations in utilisation are good markers of inequalities in access.

Additionally, the review of the relevant theories (Section 1.3) shows that it is utilisation rather than other dimensions of access that is theoretically strongly influenced by coverage of health insurance (Pauly, 1968, Einav and Finkelstein, 2018, Nyman, 2006). In reality, the related empirical studies in the literature review of this thesis all adopt utilisation as the indicator of access. As a consequence of theoretical feasibility and practical convenience, this study also uses utilisation to indicate access, reducing the multi-dimensional concept of access to a single aspect.

Nonetheless, there is more than one way to measure utilisation. According to the literature review, the concept of utilisation refers to the use of healthcare in a certain period in most studies (You and Kobayashi, 2011, Jiao, 2015, Chai, 2014, Chai, 2013, Lam and Johnston, 2012, Li et al., 2016, Yang, 2013, Qin et al., 2014, Wang et al., 2016, Yao et al., 2012, Zhu et al., 2008, Zang et al., 2012), and the length of hospitalisation in one study (Jiao, 2015). In addition, healthcare consists of several fundamental categories, such as outpatient care, inpatient care, preventative services and self-care. Due to the irrelevance of the last two to the functions of PHI, this study only places focus on the former two. In some studies, the use of either outpatient care or inpatient care is treated the same as the generic utilisation of healthcare. In other studies, they are examined separately.

In terms of this study, primarily, whether the individual has used healthcare in a certain period, the most popular measure in the related studies has been selected as the measure of the utilisation of healthcare, and hence access to healthcare. As previously mentioned, this indicates utilisation frequency, which is theoretically affected by the moral hazard less than intensity indicators such as the length of hospitalisation or total health expenditure (Nyman, 2006). The choices of healthcare types and the recall period will be discussed in more detail in the later section pertaining to operationalisation.

3.1.3 The concept of financial protection

Financial protection is “achieved when direct payments made to obtain health services do not expose people to financial hardship and do not threaten living standards” (WHO, 2018). Although it is sometimes regarded as a component of the concept of access (Evans et al., 2013), in practice it is measured independently from the access indicators (Boerma et al., 2014).

At the core of financial hardship is out-of-pocket (OOP) health expenditure, which happens at the point of health service delivery, strongly correlated with the incidence of financial risk caused by the use of healthcare (Van Doorslaer et al., 2007). The level of OOP payments for healthcare is also a direct reflection of the shortage of prepayment methods, an effective means to prevent health-related financial catastrophe (Xu et al., 2003). Accordingly, the amount of OOP payments for healthcare in a certain period is commonly applied to indicate financial risk caused by the utilisation of healthcare, and in turn reduction in OOP payments indicates the degree of financial protection of a health programme. In the literature review, this measurement was used by many included studies to measure PHI's financial protection (You and Kobayashi, 2011, Zeng et al., 2017, Jiao, 2015, Fang et al., 2012).

Nonetheless, OOP health expenditure does not sufficiently reflect the impact on a household's living level, because this measure does not involve the economic condition of the household. Consequently, another measure is created – the incidence of catastrophic health expenditure, relating (OOP) health expenditure to the household's (non-food) consumption with a threshold [17], indicating whether the household's living standard has been reduced by using healthcare (Wagstaff, 2008).

Two previously reviewed studies in this thesis selected catastrophic health expenditure (Xu et al., 2015, Wang and Wang, 2017), defining this as annual OOP healthcare payments exceeding 40% of capacity to pay – i.e. total household expenditure minus subsistence needs (represented by food consumption) (Xu et al., 2007). However, more generally, the working definition of catastrophic health expenditure varies. In addition to capacity to pay, some studies simply use total

[17] The measures of health expenditure and household consumption, and the choice of the threshold vary among studies.

expenditure (You and Kobayashi, 2011, Zeng et al., 2017, Jiao, 2015, Fang et al., 2012), while many others use total income to indicate living standards (Holst and Gericke, 2012, Zoidze et al., 2013, Bauhoff et al., 2011, Hajizadeh and Nghiem, 2011). In fact, availability of data largely determines the choice: income data tend to be more available than expenditure data, while both are more measurable than capacity to pay (Limwattananon et al., 2007). Moreover, the cut-off ratio of healthcare expenditure to the living standard measure also ranges from 5% to 40%, largely depending on countries (Krutilova and Yaya, 2012, Bos and Waters, 2008, Barros et al., 2011, Alvarez-Hernandez et al., 2012, Mills et al., 2012).

The two types of measurements both would work for the purpose of this study. By comparison, the incidence of catastrophic health expenditure provides information about the impact on living standards that the payments make. However, OOP payments capture an essential element of the financial evaluation: the extent to which insurance reduces direct payments for healthcare, and as a continuous measure, OOP payments provide more variation to be examined than a dummy measure. Practically, data constraints play a part in this choice, so more details will be presented in the section on operationalisation, associated with the available data (Section 3.5.3).

3.2 Individual factors

The determinants of outcome measures generally pertain to either the individual level or the aggregate level. This section sets out the conceptualisation of the individual-level determinants alone. The most important one is social health insurance (SHI), the public counterpart of PHI, as the literature review repeatedly highlights SHI's substantial impact on PHI, especially in prevalence (Section 2.3.2). Other individual determinants include demographic and socioeconomic characteristics, and need indicators, which will be either investigated or just controlled for as background factors.

3.2.1 SHI schemes

China's current national health insurance system is mainly based on the SHI modality (Yip et al., 2012). As one of the two general approaches towards UHC, along with the general-taxation-funded National Health Service (NHS) model, SHI is characterised by funds contributed through compulsory or semi-compulsory membership for all, with the premium paid or shared by enrolees themselves, their employers and/or the government (Carrin and James, 2005).

SHI in China was introduced in detail previously (Section 1.1.3 and 1.2.1). In brief, institutions include the Urban Employees' Basic Medical Insurance (UEBMI) (since 1998), the New Cooperative Medical Scheme (NCMS) for rural residents (since 2003), and the Urban Residents' Basic Medical Insurance (URBMI) for the urban unemployed (since 2007). In addition, the Free Medical Scheme (FMS) (since 1952) continues to cover some government employees and retirees.

It is worth noting that the introduction of SHI is a gradual process, occurring at different speeds across the country. Old public health schemes such as the urban Labour Insurance Scheme (LIS), the rural Cooperative Medical Scheme (CMS) and some fragmented urban welfare schemes once co-existed with, but eventually were replaced by, the new schemes. There are some corresponding relationships between the old schemes and the new ones. The NCMS is a new version of the old CMS. The UEBMI replaced the LIS, extending the target population from state-owned enterprise (SOE) workers to theoretically all kinds of working people (Liang and Langenbrunner, 2013). Additionally, the URBMI can be regarded as the integration of the earlier urban welfare schemes. In this study, these related schemes are counted together to avoid using an SHI variable that includes too many fragmented items to be effectively analysed.

Moreover, in this study's terminology, for simplicity, all such public insurance schemes are called SHI schemes. Strictly speaking, the FMS, solely funded by government, does not belong to the SHI modality (Carrin and James, 2005). However, public health insurance versus PHI will be investigated by this study, rather than comparisons between insurance with different contribution mechanisms. Given that both the FMS and other SHI schemes are essentially public insurance, it is not necessary for this study to classify them so elaborately in wording as to increase the burden of interpretation.

Enrolment into an SHI scheme is the natural choice for measurement, which was used in all previously reviewed individual-level studies. In the analytical model, the measure is an on/off dummy, assuming that the effect of membership of an SHI scheme is the same for all.[18] However, the literature review has suggested that variations in SHI's effects are very likely in China. In fact, the local SHI policies do vary across regions, despite the uniform guidelines and baselines set by the central government (Meng et al., 2015). Regarding the potential variations, the reviewed studies made insufficient effort to address this aspect, reasonably so, as it is extremely difficult for a study in China, especially one assessing nationwide data, to include such detailed information as the measurement of SHI benefits region by region. While also being constrained by data, this study nevertheless attempts to reflect the regional disparities to some degree by stratifying population by regions, which are explicitly different in geographical and economic terms. This will be elaborated upon later.

3.2.2 Other individual determinants

There are, in theory, very similar individual-level determinants of PHI prevalence, healthcare utilisation and OOP health payments, because the demand for PHI is largely based on the aversion to the potential risk of financial loss (i.e. OOP payments for healthcare) due to using healthcare (Pauly, 2007: 31) and the expected welfare gain from additional access generated by health insurance (Nyman, 2006). In

[18] There is the same problem for the dummy variable of PHI enrolment, though unlike SHI, PHI plans are commonly managed centrally by large insurance companies.

this sense, healthcare utilisation is the cause of the other two, and central to the identification of the determinants of this trio.

As previously mentioned, Aday and Andersen (1974) developed the classic framework for the study of access, in which at the individual level they refer to the individual utilisation determinant model developed by Andersen and Newman (1973), (2005), based on the situations in the United States. Some studies of healthcare utilisation in China referred to this model (Chai, 2014, Liu et al., 2003). Under their framework, the individual determinants of utilising healthcare are categorised to three groups. The first group is called predisposing factors, including demographic characteristics such as age, gender and past illness, social structure such as education, race, occupation, household size and religion, and beliefs such as attitudes towards health services and knowledge about health and illness. The second group is enabling factors, including household conditions such as income and health insurance, and community conditions such as health resources in the neighbourhood, the price of health services, and regions. The third group is illness level (or needs-based) factors, including perceived and evaluated health status (Andersen and Newman, 2005).

Furthermore, the framework requires slight adaption to fit China's situation. According to the literature review of empirical studies, the popular determinants in models usually include the predisposing factors, such as age, gender, education, occupation and household size; the enabling factors, such as household income, health insurance coverage and local health facilities availability; and the needs-based factors, such as self-reported health status and the diagnosis of chronic diseases (Chai, 2014, Liu and Wang, 2012, Liu et al., 2011b, You and Kobayashi, 2011, Zang et al., 2012).

In addition, the domiciles registered in *hukou* – a distinctive household registration system in China, considered in some but not all reviewed studies (Zang et al., 2012, Qin et al., 2014, Yang, 2013, Fang et al., 2012) – are also included in this study, representing a determinant. As a remainder of the planned-economy era, *hukou* primarily divides individuals into agricultural (rural) residents and non-agricultural (urban) residents in favour of rationing rural land, staple foods and urban welfare. Conversion of rural and urban *hukou* is restricted to a few channels in order to control domestic migration (Liu, 2005). Nowadays, the ration system has been long abolished, but *hukou* persists and plays a role in the entitlement to some benefits, sometimes including health services (Liang and Langenbrunner, 2013). Particularly, the registered place in *hukou* (rural) and the actual residence (urban) represent good tools to identify (rural-to-urban) migrants, who tend to be socioeconomically disadvantaged and may face difficulty in accessing urban SHI and hence healthcare in cities. A considerable number of rural-to-urban migrants may continue to be members of the rural NCMS, which faces a reduction in compensation in urban hospitals, if they cannot find a job in formal sectors to entitle them to the UEBMI (Cheng et al., 2014).

3.3 Aggregate factors

The outcome variables are influenced by not only individual characteristics, but also aggregate factors, which are important to examine as reducing regional disparities is highlighted as a key target by the current health reform policies (Yip and Hsiao, 2009a). The first part of this section focuses on the conceptualisation of the broad features that capture the key factors of regional disparities in China, and the second part attempts to provide a deeper analysis into the concrete local conditions that may influence the outcome measures.

3.3.1 Geographies and urban/rural classification

The introductory chapter briefly outlined the persistent regional disparities in the health system, which can be traced back to its early stages in the 1950s and the 1960s, when distinctly separate institutions were established in urban areas and villages (Section 1.1.1). The following economic reforms enlarged the economic gap across China (Sun and Dutta, 1997), which in turn affected local health financing and delivery (Liang and Langenbrunner, 2013), due to the decentralised health system that resulted from the economic reforms in the 1980s and 1990s (Daemmrich, 2013).

Economic disparities between the east coastal provinces and inland provinces, and between the urban areas and rural areas, are evident. According to state statistics (National Bureau of Statistics, 2013), in 2012, the urban individual average disposable income in the east coastal provinces was ¥29,622 (¥1≈ £0.11 or $0.14), while inland figures, i.e. for the central, west and northeast provinces, were ¥20,697, ¥20,600 and ¥20,759, respectively. In terms of rural individuals' average net income, this was ¥10,817 for the east coast, and ¥7,435, ¥6,027 and ¥8,846 for the central, west and northeast provinces, respectively.

Extending to health, according to official statistics in 2014, there were 10.63 urban health practitioners per 1,000 people in the east, 9.01 in the central provinces and 8.73 in the west provinces, while in rural areas, there were 4.11, 3.44 and 3.8 in the east, central and west provinces, respectively (National Health and Family Planning Commission, 2015b). The disparity between urban and rural areas is also embodied in the numbers of hospital beds: 7.84 in urban areas and 3.54 in rural areas per 1,000 people. In terms of individual health expenditure, urban residents spent approximately twice as much as rural residents, but the disparity was smaller as a percentage of their total consumption. East coastal provinces showed significantly higher health expenditure per capita than inland provinces (National Health and Family Planning Commission, 2015b). According to the National Health Service Survey (NHSS) in 2013, residents in east or urban areas were less likely to report health problems than inland or rural residents (National Health and Family Planning Commission, 2015a).

Weak evidence from the literature review supports the impacts of these regional factors on the prevalence of PHI. It generally shows that east and urban residents are more likely to buy PHI than their inland and rural counterparts, basic individual characteristics being equal. Some authors attributed the difference to regionally unequal accessibility of PHI due to commercial insurers' bias against undeveloped regions (Liu and Wang, 2012, Qu and Wang, 2010), and one author suggested that PHI sellers may market their products more intensively in more affluent regions (Liu and Wang, 2012).

The literature review finds a few reviewed studies considered geographical and urban/rural variables in their research models for healthcare utilisation or healthcare expenditure, but their outcomes are too vague and too inconsistent to extract an explicit conclusion (Section 2.3.3 and Section 2.3.4). Notwithstanding this, the related spatial inequalities are potential. As the 2013 NHSS suggested, in terms of healthcare utilisation in the last two weeks prior to taking the survey, in the east, the disparity between urban and rural areas in healthcare utilisation is tiny (15.4% versus 16.1%), while in the west it is significant (15.8% versus 11.0%) (National Health and Family Planning Commission, 2015a). Another official report showed that residents in east provinces or urban areas spent more per capita than those in inland provinces or rural areas, respectively, but it lacks data about OOP health expenditure (National Health and Family Planning Commission, 2015b).

In conclusion, though the literature review provides partial evidence about the regional impacts on the conceptualised outcome measures, plenty of data from other sources, as presented above, has suggested that there are sound reasons for including a geographical variable, particularly indicating the east and inland division, and a variable indicating the urban and rural division in this study, and hence multilevel models that take account of these may be a good choice. In another sense, this is valuable for filling the gap, because it has not been adequately documented in the literature.

3.3.2 Local factors

Although geographies and the urban rural division represent an element of the variation, they are too crude to capture more detailed variation. In the classic model of healthcare access, apart from individual determinants, healthcare utilisation is also theoretically influenced by the characteristics of the health delivery system, which consists of available resources in, and organisation of, the health system (Aday and Andersen, 1974). In other words, they involve the quality, availability and accessibility of health facilities and services in the region where the individual resides. The UHC monitoring project in China also shows that utilisation relies partly on availability and density of local health services, in addition to individual factors such as health status and health insurance coverage (Meng and Xu, 2014).

On top of these, utilisation of healthcare interacts with the consumer satisfaction, which is decided by convenience, costs, coordination, courtesy, information and quality (Aday and Andersen, 1974). Since the satisfaction as an outcome measure is not within the scope of this study, I only pay attention to the influence of the satisfaction on utilisation. On the one hand, the satisfaction itself is an individual experience and perception, which, if measurable, could be added into the analytical models. On the other hand, as suggested above, it can be disaggregated into some environmental factors that influence consumer satisfaction, such as the amenity of facilities and quality of services, and thereby impact the demand for healthcare utilisation.

Unlike individual determinants, which are conceptualised together for the three outcome measures, the aggregate determinants of the prevalence of PHI may be to some extent distinct from those of utilisation and expenditure. For example, the regional availability of PHI supply, which influences its prevalence, may have little direct impact on utilisation and hence expenditure. Contrarily, the local transportation conditions may influence the accessibility of health facilities and hence utilisation of healthcare, but hardly affect PHI purchase. Very few reviewed studies associated the prevalence of PHI with concrete local factors. Only one study showed that PHI density (indicated by provincial PHI premium income per person, related to prevalence, as discussed before) is correlated to the availability and quality of health facilities and population density (Suo et al., 2015). Good facilities may encourage utilisation so as to increase the need for financial security, and high population density could reduce the cost of marketing PHI and hence increase sales (Suo et al., 2015).

Empirically, a few studies associated individual utilisation with the accessibility and quality of local health facilities (Chai, 2014, Yao et al., 2012). These factors may partly explain the regional variation in utilisation. As the NHSS report showed, in the east, 72.1% of urban households and 63.2% of rural households are in places where the nearest health facilities are located within less than one kilometre. By contrast, in the west, while 66.3% of urban households are less than one kilometre from health facilities, in rural areas the percentage is only 47.0%. Additionally, 19.4% of western rural households require more than twenty minutes to travel from their home to the nearest health facilities, while only 3.5% of east rural households and 9.5% of west urban households do so (National Health and Family Planning Commission, 2015a). This echoes the aforementioned greater urban–rural utilisation disparities found in the west than the east. In addition, it has been well documented that the local economy, which determines the average income and price, influences total health expenditure (related to utilisation, as discussed in the literature review) (Newhouse, 1977, Roberts, 1999). Finally, OOP payments have a strong correlation with utilisation and health insurance coverage as framed in the theory review (Section 1.3.3). Those aggregate determinants applying to utilisation and PHI enrolment ought to apply to OOP expenditure as well.

3.4 Data

This study relies mainly on data from the China Health and Nutrition Survey (CHNS), a collaboration of the Carolina Population Centre at the University of North Carolina at Chapel Hill and the National Institute for Nutrition and Health at the Chinese Centre for Disease Control and Prevention. Apart from the CHNS, some other datasets, potentially applicable to this study, were identified by the literature review as well. In this section, these candidate datasets are briefly compared in order to explain why the CHNS was ultimately selected, followed by a detailed introduction of the CHNS's survey design, data collection, data extraction, ethics and weights.

3.4.1 Rationale of dataset choice

This study requires longitudinal data properly representative of China. According to the literature review, and as far as I know, there are four datasets that potentially meet this need. They are the CHNS, the China Health and Retirement Longitudinal Study (CHARLS), the NHSS and the Chinese Longitudinal Healthy Longevity Survey (CLHLS). The CLHLS sampled only those aged 65 or more, which is not a representative group of a general population, and hence is ruled out from the start.

Each remaining dataset has its own merits. The CHNS is a long-lasting longitudinal study since 1989 and it provides open access to its data. In addition, it has been widely used by previous studies, contributing greatly to literature. The CHARLS is a brand-new project with open access. It has a larger sampling scope and size than the CHNS, and generates data stably every two years. The NHSS is official as a result of its government background and has the largest sample size, covering 31 provinces.

However, each dataset has disadvantages as well. The CHNS has lasted so long that it is characterised by imbalanced panel data. Furthermore, its latest publication is the

2011 survey wave.[19] Regarding the CHARLS, its nationwide survey did not start until 2011, and so did not cover the early stages of the scale up of SHI. Additionally, its omission of those aged below 45 would be a problem for certain studies. In terms of the NHSS, access is a serious problem. In theory, academics can gain access to it in the lab of the National Health and Family Planning Commission (previous Ministry of Health) by applying and reporting variables of interest. However, according to the earlier literature review, the NHSS was used rarely, and those who used the NHSS individual data had affiliations to some extent with government institutions, suggesting that this theoretical channel may present difficulties due to bureaucracy.

This study finally selected the CHNS. Open access was one of the reasons. By contrast, selecting the NHSS would have presented the risk of failing to access the necessary data. Apart from this, the CHNS effectively covers data in the 2000s, the key stage of health reform and the development of SHI, satisfying the purpose of this study, which considers SHI to play a key role in determining the three outcome measures. At the beginning of my PhD project (2014–2015), I expected to gain access to the 2013 data in 2016, after the organiser of the CHNS replied to me via email that this would be the case. Unfortunately, there appears to be no 2013 data, and the 2015 data was released in April 2018, when the thesis had almost been completed. Nonetheless, the 2000, 2004, 2006, 2009 and 2011 data covered the crucial period of health reform, and this was sufficient for the research.

It is worth noting that while the CHARLS is an excellent dataset with an increasing number of users, it is not suitable for this study due to a lack of data before 2011. Since SHI's population coverage reached more than 95% of the population in 2011 (Meng et al., 2012), non-enrolees of SHI after 2011 would be too few to make effective comparisons with enrolees of SHI. Moreover, from 2000 to 2011, the composition of

[19] Data of the next survey wave were released in mid-2018, when the draft of this thesis has been done.

enrolees and non-enrolees of SHI might have undergone such a considerable change that it would become valuable for investigation, while after 2011 there appears to be little variation left for analysis.

3.4.2 Introduction of the CHNS

The following information is mostly derived from the official website of the data source (CHNS, 2017).

Survey design

The survey used a multistage, random cluster design. Between 2000 and 2009, nine provinces out of 31 provinces in China were sampled, geographically covering the east coastal areas and the central-west inland areas, and economically covering affluent provinces such as Jiangsu and Shandong, and poor provinces such as Guizhou and Guangxi (Figure 3.2). The 2011 wave of the survey added three provincial municipalities: Shanghai, Beijing and Chongqing. However, this study only includes the former nine provinces for analysis, because the newly added provinces are not suitable for longitudinal analyses, since they only have one wave of data.

Figure 3.2: The sampling map. The nine named provinces are sampled in the CHNS and used by this study. In China's statistical tradition, provinces in yellow belong to the west, those in green are central, and those in blue belong to the east (the coastal region). The black line is called Hu-Huanyong Line, first described by Chinese population geographer Hu Huanyong in 1935, when approximately 96% of the population lived east of the line. By 2002, this number had slightly changed to 94%.

Counties in provinces were stratified by income (low, middle and high), and four in each province were randomly selected with a weighted sampling scheme. Additionally, the provincial capital and a lower-income city were selected, except in two provinces, where other large cities were selected, rather than provincial capitals. Villages and townships within the counties and urban/suburban neighbourhoods (communities) within the cities were selected randomly as the primary sampling unit (PSU). The total number of PSUs ranges from 190 in 1989 to 291 in 2011, with the proportion of urban neighbourhoods, suburban neighbourhoods, townships and villages being 1:1:1:3, following the real contemporary distribution of the population. Within each PSU, 20 households were randomly selected. In 1989, the CHNS included 15,917 individuals from 3,795 households. In the following waves of the survey, despite attrition, the numbers of individuals and households were basically maintained by adding new households.

Data collection

The data of the CHNS was basically collected through individual, household and community (neighbourhood) interviews over a seven-day period. For individual interviews, all individuals within a selected household were interviewed with a series of designed questionnaires, including health and nutrition for all members, physical activity for children, occupation for adults, and activities of daily living and cognition for the elderly. For household interviews, the master of the household was asked questions on demographic, economic, time-use and labour force participation information. In addition, in the health section, information was collected about insurance coverage, the availability of medical facilities, curative care and illness information with associated time and money costs, preventative care with a focus on immunisation, and the use of family planning and other preventative services. For community interviews, a knowledgeable respondent of the community was asked information on community infrastructure, services, population, prevailing wages and related variables.

Data extraction

The downloadable data of the CHNS was contained in 48 datasets of longitudinal files of various themes, including one master ID file, two master physical exam and physical activity files, six master diet and infant feeding files, nine agricultural files, ten income-related files, one time-use file, two childcare files, five ever-married women files, one child/parent relationship file and three health services files.

For the purpose of this research, the datasets involving health-related, socioeconomic and demographic information were selected. The themes used were individual ID, survey sample information, healthcare, medical insurance, education, individual income, household income, jobs, physical exam, roster file and urban index, respectively. Within these selected longitudinal sets of data, only the 2000, 2004, 2006, 2009 and 2011 waves of data were extracted. In addition, I only included cases aged 18 or over for analyses, where the cause of variation in PHI purchase, healthcare utilisation and expenditure between adults and children would be fundamentally different, even if all other factors were accounted for. The cases of children, which in fact only account for a small portion of the sample, however, would not be relevant for general discussions of determinants for PHI enrolment, utilisation of healthcare and related payments.

Ethics

The CHNS project was approved by the ethics committee of the University of North Carolina at Chapel Hill. Using its data with registration and proper citation is legal and ethical. The only potential issue was that, according to the CHNS notification, the use of any data that could be used to deduce the survey location requires the approval of the local institutional review board or ethics committee. However, extracted data in this research did not involve community identifiers. Thus, there was no ethical concern at all.

Weights

There are no special variables of weights to make data representative of China or those included provinces in the CHNS, according to the project organisers, who provided two reasons (Popkin, 2014). One reason is that the State Statistical Office of China does not share its sample frame with the CHNS survey team. The second reason is that they do not believe they can create even cross-sectional sampling weights, let alone longitudinal ones. The survey design used extant census data for the multilevel random sampling. The project organisers gave two suggestions. The first suggestion was to include community-level measures as controls. The second recommended clustering data at the community level so as to adjust the standard errors and variance of estimates. This study has followed these suggestions.

3.5 Operationalisation

This section sets out to transform the conceptualised outcome measures and their determinants to operational variables, in relation to available data from the CHNS.

3.5.1 Health insurance variables

Health insurance variables include one outcome variable – enrolment in PHI[20], and several independent variables – enrolment in one of SHI schemes. According to the questionnaire of the CHNS survey, the respondents were asked two questions about their health insurance coverage status: (1) "Do you have medical insurance?" (2) "Which of the following types of medical insurance do you have?" Only those who gave a positive answer to the first question were required to answer the second one, where multiple responses were allowed. These insurance variables are binary, indicating whether the individual was covered by the specific scheme.

The PHI variable is easy to generate, as its concept and corresponding option in the survey's questionnaire remains the same throughout the five waves. By contrast, as health reform proceeded, public schemes in the questionnaire partly changed, with the generation of more than ten options between 2000 and 2011 altogether. As previously mentioned, those public schemes are conceptualised together with their respective successor scheme (Section 3.2.1) to reduce data fragmentation for the model analyses. As a result, four (new) variables arise. Specifically, the urban

[20] It is also an independent variable for other two outcome variables.

employees' scheme represents any of the worker's compensation schemes in 2000–2004, three models of urban employee medical insurance in 2006 and the UEBMI in 2009–2011. The urban residents' SHI scheme represents any of urban fragmented welfare schemes. The NCMS represents any of the rural CMS or succeeding NCMS. The governmental FMS remains intact.

Furthermore, the two urban SHI schemes are combined to form one urban SHI variable. The combination results primarily from a technical difficulty; that is, the insufficient number of members of the urban residents' scheme, which would cause computing techniques such as multiple imputation and multilevel modelling to struggle. Since this study is more interested in urban/rural disparities than those between the urban employees' SHI scheme and urban residents' SHI scheme, combining the two urban schemes to be one can increase observations, which is especially crucial for models with a multilevel structure.

It is worth noting that individuals can be enrolled in only one of these SHI schemes in theory. However, in the CHNS, a small number of individuals reported being covered by more than one SHI scheme, cases probably due to mistakes of recall or administrative errors. For such cases, only one membership was kept, according principally to their actual residence. For example, only the membership of the urban SHI was retained for those who lived in the urban area and reported enrolment of both urban and rural SHI, and vice versa. Moreover, for very few cases, where individuals reported enrolment of both FMS and one other SHI scheme, FMS membership was retained for its outstanding generosity. Consequently, the SHI variable is in effect a categorical variable with four responses: none, government officials' FMS, urban SHI and rural NCMS.

In the previous review, the theoretical literature suggests that the degree of financial protection of health insurance, and likely utilisation, are influenced by the concrete compensation policies of health insurance (WHO, 2010b, Pauly et al., 2009, Aday and

Andersen, 1974). However, the CHNS dataset does not include any variable that give information about benefit coverage of health insurance. Our relevant analysis can only proceed by comparing types of health insurance and associate the results to background knowledge about their benefit packages. This, after all, is a limitation of the study.

3.5.2 The utilisation variable

In terms of utilisation, the CHNS respondents were first asked “During the past four weeks, were you sick or injured?” Those who gave “yes” answers were further asked “What did you do when you felt ill?” with the choices of self-care, seeing the local health worker, seeing a doctor, paying no attention, or “unknown”. For those who did not feel ill, they moved on to a simpler question: “Did you seek care from a formal medical provider during the past four weeks?” This was asked because they might have still used health services for other purposes, such as chronic disease management.

Based on the answers to the three questions, one binary variable – whether the individual had used formal healthcare in the past four weeks – was generated. Those who felt ill and saw a health professional (either the local health worker or a doctor), and those who did not feel ill but still sought care from a professional, are considered together as those who used formal healthcare. Those who did not see a health professional and those who did not feel ill, and consequently did not answer the following questions, are considered together with those who did not use formal healthcare.

It is worth noting that the CHNS includes a question that distinguishes outpatient and inpatient utilisation, based on the answers to which this study could have divided formal healthcare into outpatient and inpatient care. However, the frequency of the use of inpatient care from the dataset was too low (611 observations) to be fit for disaggregation. This problem, to a large degree, relates to a rule of the CHNS measurement, which only counts events such as illness or injury and use of healthcare occurring in the four weeks before the interview. This approach is common in health surveys, with the advantage being that respondents are likely to recall details precisely in this short period, as opposed to a long recall period such as one year. However, this short-term measurement tends to miss infrequent events such as the use of inpatient care, and this is admittedly a limitation of the CHNS dataset as well as this study.

3.5.3 The financial protection variable

OOP expenditure on healthcare, i.e. total health expenditure minus compensation from health insurance, was primarily selected in this study. The theoretical reason for this was presented in the conceptualisation; the practical reason was that, in relation to the CHNS data, OOP payments data are accessible.

In the CHNS questionnaire, questions such as “How much did you spend on the illness or injury?” and “What percentage of these costs was paid by insurance or may be paid by insurance?” follow a question about the utilisation of a certain type of healthcare, if any. Accordingly, in this study, the total OOP payment for healthcare is computed through summing all types of gross health payments multiplied by one minus their corresponding percentage of compensation. The formula is presented as follows:

> Total OOP payments = gross formal care cost * (1 − compensation rate for formal treatment) + gross self-treatment cost + gross preventative cost * (1 − compensation rate for preventative care) + additional health payment

For cross-year comparison, the amounts of OOP payments are then inflated to the 2011 consumer price index (CPI), provided by the CHNS project as well, referring to the State Statistics Bureau. The CPI data vary between provinces and between rural and urban areas. Taking the 2009 data as an example, the formula is presented as follows:

Inflated OOP payments = OOP payments * the 2011 CPI / the 2009 CPI

It is noted that the first formula uses gross payment for self-treatment rather than payment after compensation. The reason for this is that both SHI and PHI compensation policies focus on hospital or clinical treatment, and data about the compensation rate for self-treatment was incompletely collected in the CHNS. Looking through the available data, the average compensation rate for self-treatment was only 6.7%, and the average gross self-treatment payment was between ¥142 in 2000 and ¥312 in 2011. The compensation appears relatively negligible, with little impact on the total payment. Thus, it is not worth including this rate at the expense of losing cases.

Notwithstanding the widespread use of OOP payments data, this variable cannot give a comprehensive measurement of financial protection, because it does not reflect the impact of the direct healthcare spending on living standards, as the indicator of catastrophic health expenditure does. However, calculation of the incidence of catastrophic health expenditure requires a set of annual data, including household total income or expenditure, food consumption and spending on health (Xu et al., 2007), while the CHNS only provides health payment data for the last four weeks. Due to this mismatch, it was infeasible to generate the variable of catastrophic health expenditure with the CHNS data. Indeed, according to the literature review of this study, no study based on the CHNS data used catastrophic health expenditure.

To complement the insufficiency in the measurement of financial protection, I considered to add an additional analysis of the impacts on living standards, which, in literature, are commonly indicated by cutting back on a variety of consumption or selling assets (Grosh and Glewwe, 1998, Xu et al., 2003, Van Doorslaer et al., 2007). However, there is no relevant data about consumption or selling assets, possibly because this survey project emphasises health and nutrition rather than economic measurements as its name suggests.[21]

After scrutinising the CHNS dataset, I selected the variable of the individual daily protein intake as the indicator of living standards. The logic is that measurement of the living standard includes the quality of food consumption and nutrition status (Grosh and Glewwe, 1998), which in turn can be effectively indicated by protein intake. This is supported by the literature which states that Asian developing countries have lower daily protein intake than the world average and improvement of living standards in Asia is correlated to an increase of protein intake (Zhu et al., 2005); in China per-capita protein intake increases along with the economic growth and a further increase is projected as the current level is still relatively low (Zhen et al., 2010).

3.5.4 Aggregate-level variables

Geographies and residence

Succinct geographies are preferred to a number of provinces for interpreting outcomes well. The tradition of Chinese statistics groups 31 provinces (excluding Hong Kong, Macao and Taiwan) into four geo-economic regions, i.e. the northeast[22], east (coastal provinces), centre and west (National Bureau of Statistics, 2013). There is an evident multi-faceted gap between the rich east and the three inland regions, as shown in the conceptualisation (Section 3.3.1). To divide urban and rural residence, in the CHNS, PSUs were classified into cities, suburbs, towns or villages. Meanwhile, it also provided a simpler variable, which grouped communities of cities and towns

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[21] The CHNS data include a household expenses variable. However, this variable is the sum of five sources of expenses including business, farming, fishing, gardening and livestock (CHNS Household Income Variable Construction. UNC Carolina Population Center.). Therefore, it is an indicator of costs of household earnings more than household consumption, and hence is not a proper indicator of living standards.

[22] Regarded as centre in earlier statistics, where China is divided into three geographic regions: east, centre and west.

into urban communities, and communities of suburbs and villages into rural communities. This study selected the simpler binary variables for both geographies and residence. Consequently, while the urban/rural variable is the original in the CHNS, the newly-generated geography variable categorises sampled Liaoning province, Jiangsu province and Shandong province to the east, and Heilongjiang province, Henan province, Hubei province, Hunan province, Guangxi autonomous region and Guizhou province to the inland.

There are three reasons for this choice. First, economic and health disparities between coastal and inland regions, and between urban and rural areas, are evident in official statistics as previously stated (Sun and Dutta, 1997, National Health and Family Planning Commission, 2015b, National Health and Family Planning Commission, 2015a). By contrast, such statistics among inland regions are mostly closer than in comparisons between them and the east (Meng et al., 2012, National Bureau of Statistics, 2013). Thus, the binary variables would be effective enough to capture the essence of the geo-economic differences. Greater fragmentation would potentially increase difficulty in interpretation. Second, this study could disaggregate the population by using the two dummies simultaneously, in effect generating four subpopulations to reveal regional disparities. Third, this study relied greatly on the multilevel models, which can effectively distinguish regional effects.

Community development indexes

In the CHNS, except provinces, the community (PSU) and the city or county to which the individual belongs is not named, so it is impossible for users to bring external regional-level data in this research. Nevertheless, the CHNS organisers have developed a scale to measure the development of communities in multiple facets, referring to psychometric methodology, which measures subtle variations on a continuum (Vlahov and Galea, 2002). The CHNS organisers suggested using the community-level measures as a complement to the simple urban/rural classification to describe community characteristics (Jones-Smith and Popkin, 2010).

The scale contains twelve components, including population density, social services, health infrastructure, modern markets, traditional markets, transportation infrastructure, communications, housing infrastructure, sanitation, economic activity, education and income diversity (Jones-Smith and Popkin, 2010). As a variable, each component was marked from zero to ten. The higher the score is, the higher the level is achieved by the community. The information used to generate these components was drawn from the CHNS household survey and the community survey. The reliability and validity of the scale were evaluated by the organisers (Jones-Smith and Popkin, 2010, Attard et al., 2012) and other academics, including a systematic review (Cyril et al., 2013), demonstrating that it does effectively indicate the community's development level.

According to the conceptualisation of local factors (Section 3.3.2), the prevalence of PHI can be influenced by aggregate factors, such as local population density, availability of insurance sellers and quality of health services. Therefore, in relation to this available community data, the population density component, the social services component and the health infrastructure component were included as the aggregate variables in the models for the prevalence of PHI. Meanwhile, the aggregate determinants of health utilisation were conceptualised to be the quality, accessibility and costs of health services, corresponding to the health infrastructure component, the transportation infrastructure component and the economic activity component, respectively. Finally, all these aggregate determinants of PHI prevalence and health utilisation apply to OOP health expenditure, and hence the models take into account all five community development components.

Theoretically, the models should have included more detailed aggregate variables indicating the volume of local healthcare resources, the forms of organisation of healthcare delivery, as well as the local price level, convenience and amenity of health services (Aday and Andersen, 1974). However, they are not available in the CHNS data.

3.5.5 Other variables

The remaining variables were mostly derived from other conceptualised individual-level determinants of utilisation (Section 3.2.2), basically following the classic utilisation determinant model (Andersen and Newman, 1973, Andersen and Newman, 2005). This study adapted them to the context of China and categorised them into new groups.

The first group contains demographic characteristics such as age, gender and household size, similar to the predisposing factors in the classic model. The second group contains socioeconomic factors such as household income, education level, *hukou* status and occupation, similar to the enabling factors in the classic model. The third group are, likewise, need or illness level variables such as chronic disease history and current health status. Most of them have corresponding variables in the CHNS, while a few were transformed from the original variables.

There are some determinants identified by the classic model that should have been included in the analytical models, but unavailable in the CHNS data. They are mainly the predisposing factors including values concerning health and illness, attitudes toward health services and knowledge about diseases. What an individual thinks about health may result in differences in inclination toward use of healthcare (Andersen and Newman, 2005), and thereby influence the expected expenditure on health and the demand for PHI.

Furthermore, since this study used longitudinal data, it considered the year of data collection a categorical variable, indicating 2000, 2004, 2006, 2009 and 2011, respectively. Basically, it was used to capture unobserved changes in variation over time, for the sake of the explanatory power of the models. It can also be used to mark the occurrence of important events in health policy during the period under study. This makes it possible to compare data before and after a certain time point. As a result, the operationalised variables are presented in the following table (Table 3.1).

Table 3.1 Summary of operationalised variables

Variable	*Type*	*Description*
		Dependent variables
PHI	Binary	Whether enrolled in a private health insurance plan
Healthcare Utilisation	Binary	Whether used formal healthcare (either outpatient or inpatient) in last four weeks
*Health expenditure **	Continuous	Total out-of-pocket payments for use of healthcare in last four weeks, inflated to 2011 CPI
Protein intake	Continuous	Average grams of daily protein intake in past three days
		Independent variables
Year	Categorical	The year of data collection: 2000, 2004, 2006, 2009 or 2011
Aggregate variables		
Geography	Binary	The region to which the province where the individual resides belongs: eastern coast or central-west inland (reference)
Community type	Binary	The type of community where the individual resides: urban or rural (reference)
Population	Continuous	An index of population density of the community
Social services	Continuous	An index of availability of private and public health insurance and provision of childcare in the community
Health infrastructure	Continuous	An index of quantity and quality of health facilities in or nearby the community
Transportation	Continuous	An index of quality of roads, and distance to bus stops and train stations
Economic activity	Continuous	An index of wages for male workers and percentage of non-agricultural population
Demographic variables		
Age	Continuous	The years after birth
Gender	Binary	Male or female (reference)
Household size	Count	The number of household members
Socioeconomic variables		

Household income †	Continuous	Log-transformed household gross income inflated to 2011 CPI
Education	Categorical	The highest education level: none or primary school, middle or technical school, or university or higher
Hukou	Binary	The place the individual is registered in: rural or urban (reference)
Working	Binary	Currently working or not
Need variables		
Health status	Binary	Whether felt ill or injured in last four weeks
Chronic diseases	Binary	Whether had a diagnostic history of chronic diseases including diabetes, high blood pressure, myocardial infarction, apoplexy and bone fracture
SHI variables		
SHI	Categorical	Whether enrolled in a public health scheme: none, FMS, urban SHI or rural SHI (NCMS)
* Unit: Chinese Yuan (¥) † The log-transformation is based on the amount of Chinese Yuan.		

In the end, it is worth noting the potential selection into health insurance, as the review of the relevant theories suggests that enrolment into PHI could be influenced by adverse selection, risk selection, capacity to pay, and even knowledge about insurance (see Section 1.3.2). Enrolment into SHI is also determined by regional implementation of the decrees of the central government (Liang and Langenbrunner, 2013). As a result, the characteristics of health insurance enrolees may differ from non-enrolees and differ among types of health insurance, undermining the estimation of the beneficial effects of health insurance coverage. Following the class framework of studying access and utilisation (Aday and Andersen, 1974, Andersen and Newman, 1973, Andersen and Newman, 2005), the identification and inclusion of model variables should help to control for these characteristics to some extent. In addition, the multilevel models for analysing utilisation and the hurdle models for analysing financial risks would help to deal with the clustering of insurance take-up and the utilisation selection problem (more details will be presented in the next chapter).

Despite these efforts, since this study is based on non-experimental data, it is still possible that enrolment into health insurance is not exogenous. This may imply the instrumental variable approach. However, on the one hand, in practice, the instrumental variable regression is incompatible with multilevel structure and hurdle models in common statistic software. On the other hand, because the theories indicate that the selection mechanisms of enrolment into insurance, especially PHI, are complex, choosing the instrumental variable could be very difficult. Therefore, this study does not use the instrumental variable approach. In fact, most of the reviewed empirical studies did not introduce instrument variables (see Appendix A). For this reason, in interpretation of the findings, causal inferences are presented careful.

Chapter Four: Data Preparation and Modelling

This is the second methodology chapter of this study, comprising three sections: the manipulation of data extracted from the CHNS dataset, handling missing data, and modelling strategies. Most processes were realised in the statistic software *Stata*, provided by the School of Social and Political Science at the University of Edinburgh.

The short first section introduces the routine process of data manipulation, in order to generate the variables for analyses, including data exploration, variable generation and recoding. The second section is the largest part of this chapter, focusing on handling missing data. Although *ad hoc* strategies have been widely used in earlier studies, this study employed an algorithm-based method called multiple imputation to address missing data. The rationale, procedure and outcome test of multiple imputation of data are elaborated. The third section outlines specifications of models for the research questions and the disaggregation of the population.

4.1 Data manipulation

Generating computable variables requires several steps of data manipulation, because data downloaded from the CHNS website are raw and segmented into several datasets. As this process is routine but long and labour-consuming, only its key components are briefly outlined here for simplicity.

4.1.1 Merging datasets

In the CHNS, as aforementioned, downloadable data are packed and compressed in the longitudinal form, segmented into 48 datasets according to themes. It is necessary to select relevant datasets and merge them together into one dataset for ease of computer analysis. In this study, eleven original datasets of the CHNS were merged, with themes corresponding to individual ID, survey sample information, healthcare, medical insurance, education, individual income, household income, jobs, physical examination, roster file and urban index. There are in total 157,286 observations in this merged dataset, without duplicate cases, by reference to individual ID and wave.

4.1.2 Recoding and transformation

There are mainly three types of recoding in this study. In the first and simplest of these, categories in some original categorical variables were combined for reasons of simplicity. For example, the six categories of the original variable – the highest level of education – were reduced to three, by combining non-schooling and primary school education together, lower middle school education, upper middle school education and technical or vocational school education together, and university or college education and master's degree or higher together. This type of recoding was also applied to the utilisation variable, the geography variable, the community type variable and the employment variable.

Second, a group of original variables was combined to form one variable. Taking the generation of the SHI variable as a typical example, the four-response categorical variable was formed by integrating four binary variables, which in turn were derived from various original variables about enrolment in a particular SHI scheme (for details see section 3.5.1). This type of recoding also applied to the chronic-disease variable and the utilisation variable in part. In addition, the expenditure variable was also derived from a group of original variables, but the recoding method involved calculation, unlike the method used for categorical variables (see section 3.5.3).

Third, some missing values were filled in by recoding, by reference to other variables. For example, the original variable of PHI suffers serious item missingness, that is, cases with a value for this variable are missing but values for some other variables are available. After checking the values for another original variable (whether they had health insurance), it could be seen that those who reported that they did not have health insurance at all contributed to nearly all the missing values of the original PHI variable. This makes sense, because respondents reporting no health insurance at all would not be further asked to select the types of health insurance that covered them. Thus, these missing values of the PHI variable could be confidently recoded to "no PHI". Apart from PHI, this type of recoding applied to the original SHI variables and the utilisation variable.

On top of recoding, as aforementioned in the operationalisation section, the health expenditure variable and the household income variable were adjusted by inflation so that longitudinal comparisons across years were feasible. In addition, the household incomes were log-transformed to deal with the skewed distribution, but the health expenses were not. Because they are closely related to the requirements of modelling, the details of transforming the health expenditure variable are presented in the later modelling section of this chapter (section 4.3.3), and the reasons are elaborated in the third results chapter (see section 7.1).

4.2 Handling missing data

The missing values that can be filled in by recoding in the way mentioned above are in effect not missing. However, there are many missing values in the CHNS that cannot be addressed in this way. This is a common problem for many datasets, especially large-scale, longitudinal surveys. A report of the National Research Council of the United States notes the detriment of missing data to the scientific credibility of causal conclusion and it highlights that it is unjustifiable to assume that analysis methods can compensate for this (Little et al., 2012).

However, the significance of missingness tends to be ignored. A recent review shows that cohort studies with missing data report the issue in an inconsistent manner and most simply excluded units with missing data from the analysis (listwise deletion). Among those trying to handle missing data, a considerable number used *ad hoc* methods that have been known to produce bias, not to mention some that did not state their strategies (Karahalios et al., 2012). With considerably unbalanced panel data, the missing values in the CHNS need to be taken seriously.

The US National Research Council recommends six principles for drawing inferences from incomplete data. First, determine whether the missingness is relevant to the research. Second, formulate a causal primary measure of the treatment effect. Third, investigate the reason for missingness. Fourth, decide a primary set of assumptions about the missingness mechanism. Fifth, carry out statistical analysis following the missingness mechanism assumption. Sixth, perform a sensitivity analysis to assess the robustness of inferences under the missingness mechanism assumption (Little et al., 2012). For quantitative studies with clear research purposes, a plausible approach to handling missing data usually begins by exploring missingness mechanisms (Carpenter and Plewis, 2011), as follows.

4.2.1 An overview of missingness mechanisms

A popular classification of missingness mechanisms was originally developed by Donald B. Robin (1976), under whose framework, mechanisms causing missingness are categorised into three types: Missing Completely At Random (MCAR), Missing At Random (MAR) and Missing Not At Random (MNAR). When data are MCAR, the cause of missingness is absolutely unrelated to the research questions. When data are MAR, the cause of missingness is independent of the unobserved values, given the corresponding observed variables. Finally, when data are MNAR, it means that the chance of observing values of the variable depends on the values themselves, even after conditioning on corresponding observed variables.

If data are MCAR, complete case analysis (CCA), the default analysis method in the statistic software in which units with missing data are excluded listwise, can apply to inferential estimation with unbiased results, though information loss compromises preciseness. However, if data are MAR/MNAR, CCA tends to lead to a biased inference (Carpenter and Plewis, 2011). Still, the CCA can be valid under certain MAR/MNAR mechanisms, where the data missingness of the variable is independent of the values of the variables themselves. In other words, in a regression model, CCA is valid only if missingness is caused by the independent variables, and given these, not the outcome variable. However, this is a very strong assumption (White and Carlin, 2010). Compared to MCAR and MAR, sometimes referred to as non-informative or ignorable missingness, MNAR is informative or non-ignorable and much more difficult to handle, perhaps requiring contextual knowledge (Carpenter and Plewis, 2011).

Related to survey studies, missingness is commonly caused by participants' non-responses to certain questions. Longitudinal surveys, which have multiple survey waves, possibly include units (individuals) with all the values missing across one or several waves of the survey. In terms of characteristics, non-responses can be subdivided into four conditions (Carpenter and Plewis, 2011). First, item non-responses occur when a participant generates incomplete data by only partly answering survey questions. Second, unit non-responses occur when few data related to participant are collected, except for basic (roster) information such as ID, gender and date of birth. Third, wave non-responses occur when a participant moves out of certain waves, giving no data at all, but may re-enter in later waves. Fourth, attritions occur when a participant drops out of the survey and no longer comes back. The last two conditions are exclusive issues for longitudinal studies.

In practice, it is often infeasible and unnecessary to make clear whether a missing participant will come back, for example. Thus, a simpler classification of missingness arises, based on a key difference – whether missingness happens to all the variables across a whole wave. Accordingly, item non-responses are called within-wave missingness or item missingness, because in this case the variable values of a unit within a wave are merely partially missing. However, when unit non-responses, wave non-responses or attritions happen, all of the values of a unit are missing (except the basic information). The latter three conditions are therefore categorised into whole-wave missingness or unit missingness (Young and Johnson, 2015).

There are some experiential reasons for these issues in a survey. For example, item non-responses may result from the participants not knowing the answer or refusing to answer, or from the survey operator not asking some questions due to forgetting or procedurally omitting them. Unit non-responses arise as a result of non-contact, non-cooperation or refusal; wave non-responses and attrition can be attributed to participants' residential mobility, non-contact and refusal (Lepkowski and Couper, 2002). In the analysis of missing data, especially if the possibility of MNAR is high, it would be better to explore the missingness mechanisms in the light of such background knowledge (Carpenter and Plewis, 2011).

4.2.2 Analysis of missing data in the CHNS

This section analyses mechanisms of missing data in the CHNS, using the theory mentioned above. The analysis begins with unit missingness, which includes unit non-responses, wave non-responses or attritions, and then examines item missingness.

Unit missingness

The CHNS dataset provided nine-wave longitudinal data from 1989 to 2011 until early 2018, with a total of 157,286 observations in the dataset, each decided by a unique combination of an ID (individual) and time (the wave of the survey). However, there are 35,703 unique IDs in the roster file, suggesting that there should have been 321,327 (35,703 IDs × 9 waves) observations if the panel data are completely balanced. Minus 157,286, 164,041 observations are de facto missing due to wave non-responses or attritions. Furthermore, regarding the 157,286 existing observations, there are 31,073 observations missing for most values except the basic information such ID, age, gender and communities they belong to, making these fall into the category of unit non-responses.

Because I focus on the five waves between 2000 and 2011 in this research, narrowing scope to this period, the number of unique IDs falls to 31,369, which means the theoretically full number of observations of the panel data should be 156,845 (31,369 IDs × 5 waves). The number of the valid observations in the dataset reduces to 67,239, and 27,071 observations suffer unit non-responses (Table 4.1). From another perspective, there are 62,535 wave non-responses/attritions or 12,507 individuals missing for all the five waves, although their IDs were once recorded in this survey. For the units not missing for all, the numbers of valid observations vary from one to five. Almost all of the units with only one valid observation belong to the three newly-added provincial municipalities, i.e. Beijing, Shanghai and Chongqing.

Table 4.1 Summary of unit missingness in the CHNS dataset

	All waves	*Last five waves*
Unique individuals	35,703	31,369
The number of waves	9	5
Theoretical number of observations of a balanced panel data	321,327	156,845
Valid observations	126,213	67,239
Unit non-responses	31,073	27,071
Wave non-responses/attritions	164,041	62,535

Exploring the pattern of unit missingness, for either all waves or the latest five waves, the unit missingness in the dataset is not monotone, because some participants moved out of this survey and returned. This suggests that the unit missingness derives from not only attrition but also from wave non-responses. Although non-monotone missingness is common in survey datasets, it makes handling missing data more complex (Robins and Gill, 1997). I will talk more about this later.

Though attrition and wave non-responses are different technically, it is effectively impossible for data users to confidently distinguish them if the longitudinal survey is still ongoing, because we never know whether those who dropped out in some waves will return in the future, unless the survey organisers explicitly declare that. Instead of the data users, the survey organisers who manage the follow-up strategy may be interested in distinguishing between unit non-responses and wave non-responses because of their different causes (the former tend to be due to non-cooperation and the latter tend to be due to non-contact), which can influence the cost of the survey (Carpenter and Plewis, 2011).

Moreover, containing the basic information is a key difference between unit non-responses and wave non-responses/attrition. However, the basic-information variables are either invariant, such as ID and gender, or highly predictable, such as age. Therefore, referring to the roster file and the survey wave, they are in effect easy to be imputed for units of wave non-responses/attritions, where they are originally absent. Finally, the three types of non-responses de facto generate units providing little data for analysis, except the basic information. For the reasons above, this study adopts the simpler classification method – treating unit non-responses and wave non-responses/attritions equally as unit missingness (Young and Johnson, 2015).

Item missingness

Exploring these valid observations, item non-response occurs among most variables of interest, causing item missingness. Because my analysis is interested in data after 2000 and values in some variables are seriously missing in the early waves due to some systematic change in the survey questionnaires across the long time period, I only explore the last five waves of data since 2000. Additionally, as discussed in a previous document, considerable missing values are associated with those aged under eighteen. As a result, when focusing on the data that I will use, item missingness in most variables of interest is in general moderate (Table 4.2).

Table 4.2 Summary of item missingness		
Variables	*Missing values*	*Observations*
	Dependent variables	
PHI	1,140	66,099
Healthcare utilisation	1,191	66,048
Health expenditure	6,008	61,231
Daily protein intake	3,941	63,298
	Independent variables	
Geography	0	67,239
Community type	0	67,239
*Community development indexes**	2	67,237
Age	30	67,209
Gender	0	67,239
Household size	0	67,239
Household income	1,469	65,770
Education	7,918	59,321
Hukou	723	66,516
working	922	66,317
Chronic diseases	14,875	52,364
Health status	826	66,413
SHI	877	66,352
* a group of indexes with the same missing pattern.		

The assumption of missingness mechanisms

To explore missingness mechanisms based on observed data, we are only able to ensure that data are not MCAR statistically; we cannot ensure that they are MCAR. We also cannot check whether data are MAR or MNAR on this basis (Marston et al., 2010). Instead, what we need to do is make an assumption before using any methods to handle missingness, followed by a sensitivity test. Consequently, in this research, I checked whether the data were not MCAR first. Because there are possibly different methods to treat unit missingness and item missingness, I examined them separately.

First, considering unit missingness, as aforementioned, information about waves, residence and urbanisation indexes, as well as sex and age, is de facto known for these units as the basic information. I investigated the relationship between unit missingness and these variables with statistical methods. As a result, Chi square tests show that there are significant correlations between unit missingness and survey waves, geographies and gender (for all three correlations, $p<0.001$). Specifically, between unit missingness and waves, Cramer's V = 0.09; between unit missingness and geographies, Cramer's V = 0.09; and between unit missingness and gender, Cramer's V = -0.03. This suggests that the correlations are all weak. Likewise, T-test shows that the average ages between missing units and non-missing units are significantly different ($p<0.001$), but that the two averages are close to each other, as are average urbanisation scores.

Next, looking at item missingness, I used three outcome variables (PHI enrolment, healthcare utilisation and OOP health payment) to check that whether their missingness was not independent of a selection of explanatory variables. As a result, missingness for all three outcome variables is significantly associated to survey waves (for all $p<0.001$). The correlation strengths between waves and missingness for PHI enrolment, and between waves and missingness for healthcare utilisation, are both moderate (both Cramer's V=0.10), while for missing values for OOP health payment, the correlation is weak (Cramer's V=0.04). Significant correlations between geographies and the community type and missingness for outcome variables were found as well ($p<0.001$), but all were weak in strength (Cramer's V<0.10). Community development indexes are also significantly different between units with missing values and non-missing values for outcome variables ($p<0.01$).

Similarly, statistically significant correlations were found between missingness for outcome variables and some individual explanatory variables such as *hukou*, SHI enrolment, education levels, occupation, and health status, but most were weak in strength (Cramer's V<0.10). Significant differences in age, household sizes and household income also existed between missingness and non-missingness units ($p<0.05$). No significant correlation was found between them in gender and chronic diseases (except between missingness for OOP payment and chronic diseases).

Consequently, these results strongly suggest that, in terms of both unit and item missingness, missing data are not MCAR statistically, because of significant correlations between missingness and the values of some other variables in this study, although most correlations are weak in strength. Under the condition of non-MCAR, as discussed above, the ordinary CCA method is not likely to give an unbiased estimation. Instead, some mathematical methods for handling missing data may be necessary to prevent inference from bias (Little et al., 2012).

Next, as aforementioned, it is infeasible to check MAR/MNAR with observed data statistically; instead, I have to make assumptions based on contextual knowledge (Marston et al., 2010). Considering the condition of MNAR first, it means that missingness is contingent on its own values, even given other related observed variables (Rubin, 1976), and thus it is a serious problem that undermines research validity (Carpenter and Plewis, 2011). The CHNS organisers provide little information about missing data, except stating that missingness is mainly caused by residential mobility (CHNS, 2017), a very common problem for many longitudinal datasets (Lepkowski and Couper, 2002). Empirically, mobility may happen randomly at the individual level and is influenced by local policies at the aggregate level. Anyhow, it seems unlikely to cause the key variables of this study, such as PHI enrolment, health utilisation and the OOP health payment, to particularly lose observations with a certain range of values.

Comparatively, it seems more plausible to assume that the missingness mechanism is MAR, in which missingness is not relevant to its values given other included variables (such as factors causing residential mobility). In other words, there appears no systematic mechanism in the survey that selectively causes some data missing, depending on the values of these data themselves. Although for a variable the missing values may be significantly different from the observed values, the difference is not the cause of missingness but can be explained by other variables.

4.2.3 Potential methods addressing missingness

The analysis above suggests that CCA is likely to cause biased inference, because the MCAR assumption barely holds for the CHNS data. *Ad hoc* methods that fill in missing data, such as mean value imputation, regression mean imputation and Last Observation Carried Forward (LOCF), as aforementioned, are known to lead to biased conclusions as well. Instead, more sophisticated methods such as inverse probability weighting (IPW) and multiple imputation (MI) are recommended (Seaman et al., 2008). They both work with the assumption of MAR.

IPW rests on the idea that the propensity of responses can be predicted from other corresponding characteristics. Using this method, a logit or probit model is fitted to estimate the probabilities of responding for all units, and then these units are weighted by the inverse of the probabilities (Li et al., 2013). Although IPW is easy to apply, its efficiency would suffer from item missingness and a non-monotone mode of missing data (Carpenter and Plewis, 2011). The meaning of MAR is very complicated, requiring a missingness pattern to occur only depending on observed data under this pattern (Robins and Gill, 1997). When MAR holds, the common strategy in IPW that uses data from previous waves to predict probabilities of responding is problematic under non-monotone missingness (Sun and Tchetgen Tchetgen, 2016), which, however, occurs for the CHNS data.

Multiple imputation (MI) is another popular method of handling missing data, applicable to both unit missingness and item missingness. Its idea stems from the assumption of MAR under which the CCA model for the variable with incomplete observations regressed on other conditioning variables is unbiased. In turn, using this model, we can impute these missing values in the outcome variable. Moreover, using this method, multiply-imputed datasets, say ten, rather than one, are created to reduce the error introduced in the simulation, and for ease of estimating the variance and confidence intervals (Kenward and Carpenter, 2007). In contrast with IPW, MI can apply to arbitrary missing data patterns, with state-of-the-art methods such as data augmentation and imputation by chained equations or full conditional specification (ICE/FCS) (Twisk et al., 2013, Donneau et al., 2015).

However, whether MI can improve analysis is still controversial, especially for longitudinal data analysis (White and Carlin, 2010, Cummings, 2013). For example, a simulation study finds that MI reduces bias compared to fixed effect regression using CCA (Young and Johnson, 2015). On the contrary, another simulation study reports that MI makes little improvement to the model but produces unstable results and is computationally inefficient (Twisk et al., 2013). Additionally, some authors argue that longitudinal models using pooled time-series methods can handle whole-wave missing data in the same way as MI does, and hence imputing whole waves may contribute little to the efficiency of analysis; it may even increase the standard error (Young and Johnson, 2015, Young and Johnson, 2013, Von Hippel, 2007). Nonetheless, these arguments rely greatly on the outcomes of simulation studies, which only include analytical variables. In real-world surveys, apart from analytical variables, plenty of auxiliary variables are measured as well, which can be added into equations for predicting the missing data but excluded from analytical models. In this case, MI could increase efficiency by exploiting more information from data excluded from the analytical models (Donneau et al., 2015, Young and Johnson, 2015, Twisk et al., 2013).

In sum, it is very clear that there are missing data in the CHNS dataset, including both unit missingness and item missingness. The pattern of unit missingness is non-monotone and statistically the missingness mechanisms for many of them are not MCAR. It is plausible to assume that their missingness mechanisms are MAR, rather than MNAR, with contextual knowledge. Under this assumption, proper methods for handling missing data, rather than *ad hoc* methods or CCA, should be applied to reduce bias, as the authoritative institution suggests (Little et al., 2012). As discussed, IPW is a potential solution but issues from the non-monotone missingness restrict its application. Alternatively, MI is applicable and may improve the models, although its efficiency in longitudinal mixed models is debatable.

4.2.4 Multiple imputation parameters

Weighing up the options presented above, the MI method was applied to impute missing data in the last five waves of the CHNS, from 2000 to 2011. The multiply-imputed data were then checked by the sensitivity tests for suitability.

The popular long-form format of data analysis can lead to problematic simulations in MI, when observations are nested within individuals, where observations are correlated to each other, because these correlations are prone to being ignored by the MI process. The solution of this study is to impute the missing data with the wide form, but to then transform them back into the long form for analysis (Lloyd et al., 2013). Under the wide form, all observations of individuals aged under 18 in wave 2000 were removed due to their irrelevance to the research interests, as I discussed in previous chapters. This approach can completely rule out the mechanism of censoring data by age, which the imputation models cannot precisely reflect. Individuals with all five waves of observations missing were excluded, since they de facto provided no information for analysis regardless of imputation.

Because the MI method takes the mean and variation of all imputations, the number of imputations is essential for stability. The early suggestion is five imputations to obtain valid inference (Kenward and Carpenter, 2007), while some argue that more imputations are required (Graham, 2009). In this research, the number of imputations is twenty, as has been commonly adopted in many recent studies (Donneau et al., 2015, Young and Johnson, 2015, White and Carlin, 2010). The joint model (with data augmentation) and ICE/FCS are two methods in MI to handle non-monotone missing data. Because the joint model commonly applies to continuous variables (Donneau et al., 2015), I selected ICE/FCS, which circularly specifies a series of conditional models for variables with different distributions (White et al., 2011). To check the convergence of the ICE/FCS algorithm, I used the *chainonly* option to try a single imputation for 100 cycles. As a result, it showed that the default ten burn-in iterations were enough to achieve stationary distributions for the imputed data.

For two reasons, I did not add the variable of education levels into the imputation model, although it has missing values. First, due to historical causes in China, individuals with a university or higher degree, a category of this variable, were very scarce relative to individuals with middle level or primary level education, especially in wave 2000. As a multinomial variable, it would incur insufficient observations in estimation for multiple imputation. Second, it may be plausible to impute the missing data with the highest level of education within five observations of an individual (although this is an *ad hoc* method like LOCF), since education levels are not likely to change for adults, and it is especially impossible to move downward. By contrast, the algorithm in the multiple imputation is theoretically possible to generate unrealistic predictions in some cases.

The continuous variable of out-of-pocket spending includes considerable zeros and a long tail on the right. It would be questionable to assume that it is either a normal distribution or a negative binomial distribution. To solve this problem, I divided it into two. One is a binary variable indicating that the spending is non-zero and the other is a continuous variable of natural logged non-zero spending, in the logistic distribution and the normal distribution respectively.

I only conducted MI once, including all the variables of interest for all my research questions, rather than conducting one for each dependent variable, because the inclusions of variables for these models are mutually applicable to each other. In addition, as aforementioned, an advantage of MI is that it can bring in information from auxiliary variables that are included in MI but excluded from the analysis. In principle, these auxiliary variables should be related to unit missingness (Young and Johnson, 2015), while they should not bring in too many new missing values for technical reasons. In this sense, some community variables in the CHNS that have not been included in the analytical models are satisfactory. Consequently, the community indexes of communication development and education level are included in MI as auxiliary variables, considering that local levels of communication and education may influence the follow-ups of the survey and hence determine missingness, but are not relevant to the research questions.

4.2.5 Selection of imputed data

After imputing the missing values and transforming them to the long form, there were a total of 98,170 (19634×5) observations, with 20 imputations for each included variable in MI. Some observations were whole-wave imputations, which means that all of the values except basic ones like ID, gender and age were computationally generated. Although, as aforementioned, the efficiency of whole-wave imputations is contested because they increase computing complexity (Young and Johnson, 2015, Young and Johnson, 2013, Von Hippel, 2007, Twisk et al., 2013), it is possible to gain efficiency as long as they bring in new information from auxiliary variables (Donneau et al., 2015, Young and Johnson, 2015, Twisk et al., 2013).

This study basically kept these whole-wave imputations for the potential information gain. Except for possible inefficiency, few studies have reported that whole-wave imputations introduce bias; only one argued that it may increase individual-level standard errors (Von Hippel, 2007), which, however, is not the key concern of this research. In effect, imputing data in the wide form, as this study did, can reduce the inefficiency of whole-wave imputations, because it allows information to be precisely shared within one individual (Young and Johnson, 2015).

However, extreme cases deserve special discussion. In the dataset, there are some individuals missing in up to four waves of observations. If only one-wave information can be referred to, it would be problematic to make inferences about over-time change. Exploring these units, many of them are distributed in communities from which all observations came from a single wave. In fact, most of these communities belong to three provincial municipalities, Beijing, Shanghai and Chongqing, which were only sampled in 2011. Therefore, for these individuals in communities that have been sampled only once, neither individual variables nor community-level variables have more than one observation.

Accordingly, I dropped all units in the communities that only appeared in one wave of the survey. As a result, all observations in 76 communities were removed among the total of 297 communities, including all 72 communities of the three provincial municipalities. This method hopes to mitigate possible trouble in aggregate-level inference and maintain information for analytical models as much as possible. Though some real observations were excluded from the analysis, full information has been exploited through MI and stored in the imputed values. On the other hand, I kept the individuals who had only one observation but the communities that they belonged to had data of more than one wave. One reason for this is that in this dataset there are several community-level variables, which can provide the vacancies of individual data with external information through the process of MI. As discussed previously, this could make an improvement to the efficiency of inference (Donneau et al., 2015, Young and Johnson, 2015, Twisk et al., 2013). Another reason is that the number of these individuals is very small, meaning that this is no real issue with longitudinal models.

4.2.6 Sensitivity tests for imputed data

A sensitivity test was conducted by fitting full-variable three-level models using maximum likelihood estimation for PHI enrolment using CCA (Model 1), all imputations (Model 2), imputations excluding single-observation units (Model 3) and imputations excluding single-observation communities (Model 4) (Table 4.3). The dataset used in Model 4 is the very dataset that has been described above and it will be used in following research. Model 1 and Model 2 represent two extreme cases of handling missingness. Model 3 is a more conservative method, alternative to that used in Model 4.

As a result, despite the different numbers of included observations, individuals and communities, the outcome profiles of all four models appear consistent. Except minor variations for a few items, there is little difference in sign, significance or magnitude of fixed effects among the four models. This suggests that the fixed-effect part of the model is robust, regardless of how many imputed data are included. In terms of the random-effect part, counting in imputed data predictably increases individual-level variance (Von Hippel, 2007). Compared to the CCA model (Model 1), where the individual-level variance is far less than the community-level variance, in Model 2 the individual-level variance rises to as much as the community-level variance. Expansion of observations is a reason. As some observations are removed in Model 3 and Model 4, the individual-level variances reduce to be explicitly less than community-level variance.

Accordingly, there would be little difference between the inferences drawn from these models, except that based on the random effects of Model 2, the model with all imputations. Using different strategies for screening data, Model 3 and Model 4 would lead to similar inferences, while Model 4 takes more information into account than Model 3. As discussed above, with the notion of exploiting information as much as possible, the dataset used in Model 4 is preferable to that in Model 3.

Table 4.3 The sensitivity test for selection of imputed data

	Model 1	*Model 2*	*Model 3*	*Model 4*
Model on PHI enrolment	*Complete cases*	*All imputations*	*Imputations excluding single-observation units*	*Imputations excluding single-observation communities*
Communities	297	297	221	221
Individuals	17,985	19,634	12,019	16,351

Observations	46,765	97,120	60,095	80,471
Coefficient (S.D.)				
Cons	-4.96(0.59)***	-4.85(0.57)***	-4.72(0.60)***	-3.96(0.60)***
Year	Reference = 2000			
2004	-2.19(0.10)***	-1.98(0.11)***	-2.14(0.12)***	-2.08(0.11)***
2006	-2.27(0.10)***	-2.05(0.14)***	-2.20(0.11)***	-2.07(0.11)***
2009	-2.05(0.10)***	-2.12(0.13)***	-2.11(0.11)***	-2.04(0.10)***
2011 (Post-2009)	-1.86(0.10)***	-1.92(0.10)***	-1.90(0.11)***	-1.85(0.11)***
Age	0.06(0.01)***	0.04(0.01)***	0.06(0.01)***	0.05(0.01)***
Age^2	0.00(0.00)***	-0.00(0.00)***	-0.00(0.00)***	-0.00(0.00)***
Gender	-0.04(0.05)	-0.06(0.06)	-0.05(0.06)	-0.05(0.06)
Chronic diseases	0.08(0.07)	0.05(0.07)	0.10(0.07)	0.05(0.07)
Household income	0.22(0.03)***	0.24(0.03)***	0.19(0.04)***	0.20(0.03)***
Household size	-0.08(0.02)**	-0.10(0.02)***	-0.08(0.03)**	-0.08(0.02)**
Education	Reference = no or primary school			
Middle or tech	0.28(0.07)***	0.18(0.06)**	0.30(0.07)***	0.21(0.07)**
University	0.46(0.11)***	0.40(0.10)***	0.45(0.12)***	0.38(0.10)***
Working	0.10(0.07)	0.23(0.07)**	0.20(0.07)**	0.20(0.07)**
Hukou	-0.42(0.10)***	-0.45(0.12)**	-0.46(0.13)**	-0.47(0.12)***
SHI	Reference = no SHI			
FMS	1.79(0.09)***	1.70(0.08)***	1.84(0.09)***	1.80(0.08)***
Urban SHI	0.41(0.09)***	0.60(0.13)***	0.63(0.12)***	0.59(0.11)***
NCMS	1.07(0.10)***	1.47(0.10)***	1.38(0.11)***	1.31(0.09)***
Aggregate variables				
Geographies‡	Reference = east			
Northeast	-0.45(0.22)*	-0.39(0.16)*	-0.41(0.21)†	-0.45 (0.20)*
Midland	-0.87(0.20)***	-0.77(0.15)***	-0.81(0.19)***	-0.83(0.18)***
West	-0.95(0.21)***	-0.81(0.16)***	-0.79(0.22)***	-0.85(0.21)***
Community types ‡	Reference = city			
Suburb	-0.30(0.24)	-0.47(0.18)*	-0.52(0.24)*	-0.60(0.23)**
Town	-0.64(0.22)**	-0.67(0.17)***	-0.70(0.24)**	-0.76(0.22)**
Village	-1.59(0.23)***	-1.59(0.20)***	-1.76(0.26)***	-1.78(0.23)***
Population	0.01(0.04)	0.04(0.04)	-0.01(0.05)	-0.03(0.04)
Social services	-0.04(0.01)**	-0.02(0.01)†	-0.02(0.01)†	-0.02(0.01)†
Health infrastructure	0.05(0.02)**	0.05(0.01)**	0.06(0.02)**	0.04(0.02)*
Random effect: Variance (S.D.)				
Community-level	1.13(0.15)***	0.53(0.07)***	0.81(0.13)***	0.70(0.11)***
Individual-level	0.08(0.11)	0.53(0.10)***	0.19(0.12)	0.32(0.13)*

Data source: CHNS (2000, 2004, 2006, 2009, 2011)

FMS = government employees' scheme; NCMS = rural SHI schemes.

Significance values: †p≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.

‡For more careful comparison, the variables of geographies and community types include more items than latter analyses.

4.3 Analytical strategies

This section outlines the statistical strategies for the multiply-imputed data. Generally, multilevel models were applied to the prevalence of PHI and PHI's impact on healthcare utilisation. Nonetheless, for analyses of financial protection, other methods were employed due to the trade-off between the suitable analytical models for health expenditure data and the technical limitations of the statistical techniques. This section focuses on presenting the rationales for the choice of these analytical strategies and the basic processes of modelling the data. Some details of these processes are specified in the corresponding results chapters.

4.3.1 Basic framework of modelling

The choice of multilevel modelling was basically determined by the structure of the data, which is longitudinal rather than multiple cross-sectional. After multiple imputation, the panel data become balanced. That means that each individual has five observations. The observations within one individual cannot be assumed to be independent of each other. Likewise, individuals cannot be considered to be randomly sampled from the entire population, but instead they are actually nested in communities selected with the stratification method. Thus, it would be better to treat the individuals and communities as levels rather than to ignore their inner structure.

Accordingly, in the multilevel models, observations are the primary units, placed at the first level. The time variable, indicating when the observation was collected (2000, 2004, 2006, 2009 or 2011) is the sole first-level variable. Furthermore, every five observations are nested in one individual, at the second level. All the individual and household variables identified by the last chapter belong to this level. The communities (neighbourhoods) are defined to be the third and the highest level, because communities are primary sampling units (PSUs) of the CHNS, a multistage, stratified-sampling survey. Most of the aggregate variables in effect describe the characteristics of the communities, including the variable of urban and rural classification and the selected community development indexes.

Theoretically, provinces could have been the fourth level of this model. However, adding a level to a model would dramatically increase computation complexity on the one hand, and the number of provinces (nine) in CHNS is not theoretically sufficient to form the level of a multilevel model on the other (Centre for Multilevel Modelling, 2017). Instead, this study used the geography of the province as an aggregate variable to capture variance between coastal provinces and inland provinces. Consequently, the structure of the models is presented in Figure 4.1.

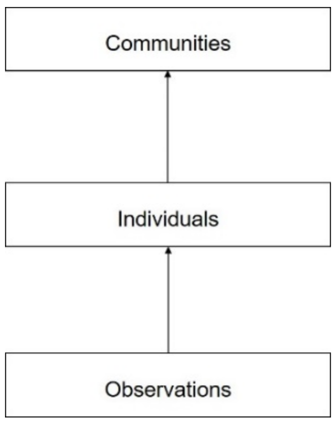

Figure 4.1: The structure of the multilevel model.

4.3.2 Justification for the longitudinal estimator

The structure above means that the longitudinal data are pooled across five time-points, with an additional level of communities. This is a common approach to analysing longitudinal data with a hierarchical structure (Rabe-Hesketh and Skrondal, 2012: 385), where the random effects estimator is applied to the estimation of both the individual and the community-level variations.

It is worth justifying the application of random effects estimator to modelling longitudinal data at first, because either random effects models or fixed effects models are possible, with different assumptions on the unobserved unit (individual) specific effects. By comparison, fixed effects models relax the assumption of exogeneity (covariates are uncorrelated with the unobserved unit specific effects), which random effects models stick to. The Hausman test can test this assumption (Hausman, 1978). The outcome of the Hausman test is either no systematic difference between the estimates of the fixed effects model and the random effects model (the null hypothesis), or the fixed effects model is preferred to the random effects model, because the fixed effects model is based on a looser assumption.

Notwithstanding the different assumptions, we could not rush to the conclusion that the fixed effects model is a safer choice than the random effects model in all circumstances. The first and primary advantage of the random effects model over the fixed effects model is that the random effects model can estimate effects of unit-level covariates, although a much greater number of units is required. The second advantage of the random effects model is that it has a loose requirement of the minimum number of observations within one unit, while the fixed effects model needs at least two (and the larger the better) within-unit observations to estimate the intercepts of units (Rabe-Hesketh and Skrondal, 2012: 159).

For the CHNS data, the number of units (individuals) is far more than sufficient for the requirement of the random effects model, whereas there are only five observations within each individual, not quite ideal for the fixed effects model. In addition, this data structure implies within-individual variation is modest, relative to between-individual variation, under which circumstances choosing the random effect model may be advisable (Rabe-Hesketh and Skrondal, 2012: 158). More importantly, the within-individual effects, as well as the between-individual effects, are of interest to this study. Nonetheless, the fixed effects model would prevent this study from investigating the effects of the variables without over-time change within the individual, particularly aggregate variables.

Finally, due to multiply-imputed data and the limitations of the statistical software's algorithms, the Hausman test is not applied in this study. After multiple imputation, twenty imputations were created, but the command built in Stata, *hausman*, is not compatible with multiply-imputed data so far. Although carrying out such a test for each imputation of the data is feasible, it would be challenging to interpret the outcomes of twenty imputations together. After all, despite the absence of the Hausman test, after the discussion above, it may be justifiable enough to use random effect models, instead of fixed effects models, because the need of the study far outweighs the outcome of a simple test. In fact, while fixed effects models are popular in economics, many studies on health, education, psychology, etc. emphasising between-individual variation, simply select random effects models without reporting the outcome of the Hausman test (Hong and Raudenbush, 2006, Kim et al., 2006, Quene and van den Bergh, 2008, Yang and Land, 2006).

4.3.3 Model specifications

The specification involves the basic components of modelling, such as the type of the model, the link of the equation, and the inclusion of variables. To avoid repetition in presentation, more delicate operations are elaborated in the corresponding results chapters, near their outcomes. It is worth noting that wording in the following results chapters, where if "effect", "impact" or "chance" is mentioned, it refers to a statistical effect in the first instance only and does not imply causality unless discussed.

Models for prevalence

Following the brief descriptive analyses of the over-time change of PHI enrolment data and the composition of PHI policy-holders, the multivariate regression models with the dependent variable of PHI enrolment were fitted. Because the dependent variable is a binary variable, the link of the equation is the logit estimator. For random effects, only the interval was allowed to vary between communities, because adding random slopes would increase the complexity of computation so dramatically that the model would struggle to converge, and this study has no particular interest in the individual-level or community-level random effects of any independent variable since the focus is PHI.

In terms of the inclusion of independent variables, the SHI variable is the most important explanatory variable. Besides, the time variable and most of the defined individual variables in the last chapter were included, except the variable of health status (whether ill or injured in the past four weeks of the survey), which appears irrelevant to PHI enrolment. Regarding the aggregate variables, as stated in the conceptualisation, in addition to the variables of geography and community type (urban/rural), three indexes of the population density, the availability of social services and the health infrastructure in the community were included.

Models for healthcare utilisation

Because the dependent variable is also a binary variable, like that in the models on the prevalence of PHI, the logit model was also applied. Based on the structure of multilevel modelling, unlike modelling PHI prevalence using solely the random-interval models, for healthcare utilisation, both the random-interval models and the random-slope models with the effect of the variable of PHI enrolment varying among communities were tried, depending on the specific question being answered.

In terms of the inclusion of independent variables, most independent variables of the models for PHI prevalence and the models for healthcare utilisation are alike. The difference is that, first and most importantly, the variable of PHI enrolment, the dependent variable of the former models, is included as a key independent variable in the latter ones. Second, the variable of health status was included, because it is an indicator of the need for healthcare, theoretically correlated with the use of healthcare. Furthermore, this variable was used to interact with the variables of PHI enrolment and SHI enrolment, respectively and simultaneously, to examine the effects of these health insurance schemes and their combination on healthcare utilisation at different conditions of need. Third, the group of aggregate variables indicating development of the community were changed to the three indexes of the quality of health facilities, the transportation infrastructure and economy.

Models for financial protection

The dependent variable, OOP payment for healthcare, is a heavily skewed and censored continuous variable with many zeros, making the choice of models and estimators sophisticated. After weighing up various options and balancing their pros and cons, the sample-selection Heckman-probit model and the zero-inflated negative binomial (ZINB) model were selected, in order to overcome the issues of data selection, heteroskedasticity and normality. Due to technical restrictions, the method of multilevel modelling did not apply to these models. Instead, variance component estimation (VCE) in which observations were specified to be clustered in the individual, was used, in order to deal with the longitudinal structure of the data. The justification for this is elaborated in the corresponding results chapter (see section 7.1).

The two types of models both require transformations of the dependent variable. For the Heckman model, the original dependent variable was transformed into two variables – whether the OOP payments were more than the median of all OOP payments and whether the OOP payments were more than the 90th percentile of all

OOP payments – to indicate moderate and high financial risks, respectively. Admittedly, transforming the continuous variable to the binary variables inevitably led to information loss. The ZINB model, where the dependent variable was merely rounded into integers as counts by taking the ceilings from the original continuous variable, was applied to complement the Heckman model.

For the inclusion of the independent variables, both the Heckman model and the ZINB model involve two equations. Regarding the Heckman model, the first equation, or the selection equation on utilisation, is effectively the same as the previous model for healthcare utilisation, and hence the inclusion of independent variables should be basically identical. Mathematically the first equation of the Heckman model must include at least one variable that is not included in the second equation (Heckman, 1979). Except this one, other independent variables in the equation on OOP payments and those in the equation on the utilisation can be the same, as the two dependent variables share very similar determinants (Liu et al., 2011a, You and Kobayashi, 2011). Consequently, the variable of health status was only included in the first equation, because it is supposed to determine seeing a doctor, but it has relatively little influence on OOP payments, which are more likely to be determined by the doctor's decision, affluence and insurance coverage, instead. This assumption is supported by the correlation analysis presented in the results chapter (see section 7.3).

The ZINB model's first equation estimates the occurrence of zero OOP payment and the second equation estimates the positive OOP payments as counts. The occurrence of zero OOP payment as the dependent variable of the first equation resembles the model for healthcare utilisation, because the latter to a great extent determines whether the OOP payment is zero. In this study the ZINB model's independent variables are exactly the same as the Heckman model for easy cross-reference, although it has no such requirement for different numbers of independent variables between two equations as the Heckman model does (Min and Agresti, 2002). On top of these, aggregate community indexes included in both the models for the prevalence of PHI and healthcare utilisation were included in the models for the OOP health payment, for the reason that has been presented previously (section 3.3.2). The included variables are summarised in the following table (Table 4.4).

Finally, the analysis of daily protein intake to examine the impacts on living standards was introduced to complement the aspect of financial protection that OOP payments do not reflect. Because the grams of protein that individuals consume daily basically follow a normal distribution, three-level linear models are selected, using the same structure described as above. As a part of analysis of financial protection, inclusion of independent variables accords with those in the models on OOP payments.

Table 4.4 The summary of included variables for the analytic models								
Variable	*Obs.*	*Mean*	*Std. Dev.*	*Min*	*Max*	*Prevalence*	*Utilisation*	*Financial protection*
Dependent variable								
PHI	81,755	0.05	0.31	0	1	+		
Healthcare utilisation	81,755	0.13	0.50	0	1		+	+*
OOP payments > 50%	10,099†	0.50	0.56	0	1			+‡
OOP payments > 90%	10,099	0.10	0.31	0	1			+‡
OOP payment = 0	81,755	0.16	0.53	0	1			+§
OOP payments as counts	81,755	155.53	2982.43	0	90543			+‖
Protein intake(in grams)	81,755	66.01	36.28	0.78	441.91			+
Independent variables								
Time	81,755	2000 = 20.00%; 2004 = 20.00%; 2006 = 20.00%; 2009 = 20.00%; 2011 = 20.00%				+	+	+
Aggregate variables								
Geography	81,755	East = 21.94%; Inland = 78.06%				+	+	+
Community type	81,755	Urban = 35.41%; Rural = 64.59%				+	+	+
Population	80,471	6.01	1.45	0.5	10	+		+
Social services	80,471	3.16	2.77	0	10	+		+
Health infrastructure	80,471	5.63	2.46	0	10	+	+	+
Transportation	80,300	5.65	2.39	0	10		+	+
Economic activity	80,471	6.29	3.29	0	10		+	+
Individual variables								
Demographic variables								
Age	81,755	48.10	16.33	18	100.8	+	+	+

Gender	81,755	0.48	0.50	0	1	+	+	+
Household size	81,755	3.96	1.89	1	13	+	+	+
Socioeconomic variables								
Household income	81,755	10.03	1.45	1.73	14.15	+	+	+
Education	80,745	None or primary school = 38.38%; Middle or technical school = 55.09%; University or higher = 6.53%				+	+	+
Hukou	81,755	0.55	0.60	0	1	+	+	+
working	81,755	0.62	0.68	0	1	+	+	+
Need variables								
Chronic diseases	81,755	0.17	0.57	0	1	+	+	+
Health status	81,755	0.14	0.52	0	1		+	+¶
Insurance variables								
SHI	81,755	None = 44.33%; FMS = 6.42%; Urban SHI = 19.74%; NCMS = 29.51%				+	+	+
PHI	81,755	0.05	0.31	0	1		+	+

The summary is based on multiply-imputed data; the observations of the education variable and some community development indexes variables are slightly less than other variables, because multiple imputation was not applied to them, as stated previously.

For categorical variables, the proportion of each category (response) is presented.

+ means the variable is included in the models for the corresponding research question.

FMS = government employees' scheme ; Urban SHI = combination of Urban Employees' Basic Medical Insurance (or its predecessors), and urban Residents' Basic Medical Insurance (or other earlier urban schemes); NCMS = rural SHI schemes.

* The dependent variable for the first equation of the Heckman model; † Only includes healthcare users; ‡ The dependent variable for the second equation of the Heckman model; § The dependent variable for the first equation of the ZINB model; ‖ The dependent variable for the second equation of the ZINB model; ¶ Only occurs in the first equation for both Heckman and ZINB model.

4.3.4 Disaggregation and community effects

Disaggregation is a tool to reflect inequality (Boerma et al., 2014). In this study, as aforementioned, following the models on the whole, the population were further divided into four subpopulations by two dichotomies, i.e. east and inland provinces, and urban and rural communities. Consequently, there are four subpopulations, i.e. the urban east, the rural east, the urban inland and the rural inland, with 26, 49, 50 and 96 communities at the aggregate level, respectively (Table 4.5). Then, four models, with the same structure and the same variables as the model on the whole, were fitted for the four subpopulations, respectively.

Table 4.5 The numbers of communities and observations after disaggregation

	East		*Inland*		*Total*
	Urban	*Rural*	*Urban*	*Rural*	
Communities	26	49	50	96	221
Observations	9,365	17,470	19,585	35,335	81,755

In principle, the early literature recommends a minimum number of 25 higher-level clusters (communities in this study) to obtain a precise estimate of between-unit variance (Paterson and Goldstein, 1991). Some later rules of thumb reduce this number to 15 (Centre for Multilevel Modelling, 2017). In any case, all subpopulations in this study meet this requirement. In terms of the effective number of within-cluster observations, there is another 25 as a rule of thumb (Paterson and Goldstein, 1991). The within-community individuals of this study are far more than enough: each community has about 70 individuals.

Additionally, to examine the contextual effects of PHI on average utilisation and OOP payments in the community, the percentage of PHI enrolees in the community was calculated to indicate PHI's coverage level in the community. For reference and control, SHI's coverage level and the average health level in the community were also calculated. All these newly-created community variables were added to the corresponding earlier models as additional independent variables, to investigate whether the effect of the health insurance scheme had extended from its enrolees to the entire local community.

4.3.5 Model sensitivity tests

Sensitivity tests were conducted to test the robustness of the coefficient estimates of the analytical models based on the whole sample, to alternations in the conditioning set of information. Except the analytical models, those that were almost the same as the analytical models but excluded demographic variables and socioeconomic variables, separately, were fitted as the test models to compare the coefficients of the variables of interest among the three. For full information, see Appendix B. Briefly speaking, for the models for PHI prevalence and financial risk, the coefficient profiles are almost similar in the analytical models and their corresponding test models. For the model for healthcare utilisation, despite differences in the substance of some variables between the analytical model and the test model excluding demographic variables and health status, significance and signs are basically unchanged. These results suggest that the analytical models are robust.

Chapter Five: PHI Prevalence, Distribution and Relationship with SHI

This chapter investigates the prevalence of private health insurance (PHI) in line with the breadth dimension of the coverage model, i.e. the population or who is covered (Boerma et al., 2014). Indeed, the prevalence is the foundation of health insurance as it decides the extent to which the whole system is impacted. The advocates of PHI, who believe in its capacity for benefiting the health financing system and preventing financial risk for individuals (Preker, 2007: 6, Sekhri and Savedoff, 2007: 241-242), would be worried about a low prevalence of PHI along with a shortage of public coverage, which would mean a high level of dangerous out-of-pocket (OOP) payments. However, the main concern of PHI's critics is that it tends to disproportionally cover rich or privileged people and transfer medical resource from those with the most needs to their affluent policyholders (Colombo, 2007: 225-226, Bos and Waters, 2008).

Chinese policymakers have defined PHI as an important complement to the publicly-run social health insurance (SHI) (State Council, 2014b, Xiang, 2014), which has expanded substantially during the health reforms, but which still leaves considerable gaps in coverage, especially in height and depth (Yip et al., 2012). Since 2000 in China, PHI insurers' total premium income has increased year on year, supplying products ranging from substitutive to complementary or supplementary (EY, 2016b, Luo et al., 2016). Many academics believe that PHI can develop well with SHI and properly address the gaps left by SHI (Li, 2009, Lv, 2013, Zhu and Gui, 2014, Wang et al., 2015).

PHI in China is nevertheless not immune from the two concerns presented in the first paragraph. The literature review of this thesis shows that PHI's prevalence is low and increases slowly on the one hand, and an unequal distribution of PHI in favour of the rich has been well documented on the other. The literature review also finds that the current body of literature relies heavily on provincial administrative data, which measure insurers' total income from PHI premiums instead of real enrolment. By contrast, the more pertinent individual-level studies give mixed evidence. Consequently, so far it has been difficult to clarify the reasons for the slow growth of PHI prevalence, as well as the extent to which PHI has been distributed unequally. This impedes weighing the advantages and disadvantages of PHI in China's UHC movement at the first step.

To overcome these problems, this study uses large-scale individual-level data with longitudinal, multilevel analyses. It hopes to provide an innovative and comprehensive perspective to investigate PHI prevalence and its determinants, linking to policies to interpret the mechanisms behind the prevalence and its consequences for equity. The first section shows a step-by-step approach of adding individual (or household) variables to the longitudinal, mixed model, followed by section two, in which the community level is combined with aggregate variables. After establishing the multilevel model, the third section disaggregates the whole population to four subpopulations to examine the spatial inequality. The fourth section investigates the temporal change of the effects of PHI's determinants, focusing on SHI.

5.1 The individual-level model

This section starts with a descriptive analysis of the individual variables in the model. Afterwards, the model on PHI enrolment is fitted step by step.

5.1.1 Descriptive analysis

The binary variable indicating whether the individual had PHI at the time the survey proceeded is the dependent variable. The key independent variable is membership of

SHI, which is a categorical variable that consists of no SHI (reference), government employees' Free Medical Scheme (FMS), urban SHI schemes and rural New Cooperative Medical Scheme (NCMS).[23] As the summary of the model's individual variables shows (Table 5.1), between 2000 and 2011 in general, about 5% of the total sample were covered by PHI, while 55.67% were covered by SHI.

Table 5.1 Overview of individual model variables

Variable	*Description*	*Mean (S.D.)*	*Min./Max.*
	Dependent Variable		
PHI	Whether was covered by private health insurance	0.05 (0.31)	0/1
	Independent Variable		
2004	The year 2004 or not	0.20 (0.40)	0/1
2006	The year 2006 or not	0.20 (0.40)	0/1
2009	The year 2009 or not	0.20 (0.40)	0/1
2011	The year 2011 or not	0.20 (0.40)	0/1
Age	Years old	48.10 (16.33)	18/112
Gender	Male or not	0.48 (0.50)	0/1
Chronic diseases	Whether had a history of chronic diseases, including high blood pressure, diabetes, myocardial infarction, apoplexy or bone fracture	0.17 (0.57)	0/1
Household Income	Naturally logged household gross income inflated to 2011	10.03 (1.45)	1.73/14.15
Household Size	The number of the household members	3.96 (1.89)	1/13
Education	The level of education: None or primary school = 38.38%; Middle or technical school = 55.09%; University or higher = 6.53%		
Working	Whether was working	0.62 (0.68)	0/1
Hukou	Whether was officially registered in rural areas	0.55 (0.60)	0/1
SHI	None = 44.33%; FMS = 6.42%; Urban SHI = 19.74%; NCMS = 29.51%		

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 81,755.
For categorical variables, the proportion of each category (response) is presented.
FMS = government employees' scheme; NCMS = rural SHI schemes.

[23] In the study, urban SHI schemes comprise the Urban Employees' Basic Medical Insurance (and its predecessor, the Labour Insurance Scheme), and the Urban Residents' Basic Medical Insurance (and other earlier urban schemes); the NCMS comprises the current rural SHI scheme and its predecessor, the Cooperative Medical Scheme. For details see Section 3.5.1

Looking at the prevalence change of SHI as a whole and PHI over time (Figure 5.1), both stood at low levels in 2000. After a slow increase between 2000 and 2004, SHI experienced a rapid expansion between 2004 and 2009, reaching a very high population coverage in 2011. On the contrary, the prevalence of PHI greatly dropped between 2000 and 2004, and very slowly increased afterwards, from 2.47% in 2004 to 3.59% in 2011, according to the CHNS data. From PHI advocates' point of view, given the long-lasting insufficient benefits of SHI coverage by UHC's standard, the lag in PHI prevalence needs policy attention (Gu, 2009b, Xiang, 2014), although for PHI sceptics this may not be a problem *per se* (Kutzin et al., 2016).

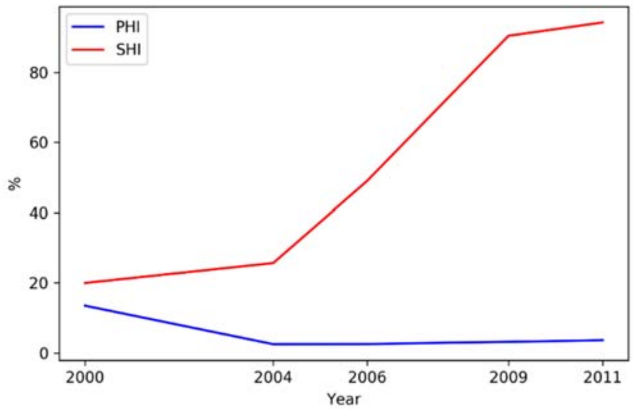

Figure 5.1: Percentages of PHI enrolees and SHI enrolees as a whole in the population in China over time. Data source: CHNS; N = 81,755.

Before modelling, the correlation matrix describes the relations between PHI enrolment and individual variables (Table 5.2), based on the pooled data. Varying in strength, being male, having chronic disease history, with higher household gross income, being highly educated and presently working are positively correlated to PHI enrolment, while age, household size and rural *hukou* are negatively correlated to PHI enrolment. Paying attention to the three SHI schemes, the government's FMS has a relatively strong positive correlation with PHI enrolment (r = 0.22), while the other two's correlations with PHI are weak (urban SHI: r = 0.02; NCMS: r = -0.04). In addition, the FMS and the urban SHI are correlated with higher socioeconomic status, such as a higher household income, a smaller household size and a higher education level, while the NCMS tends to have an opposite correlation with these socioeconomic variables, except household income. This suggests that compared to other SHI enrolees, NCMS enrolees appear to be relatively disadvantaged in socioeconomic terms.

Table 5.2 Correlations of PHI enrolment and individual determinants												
	PHI	*Age*	*Gender*	*Chronic diseases*	*Household income*	*Household size*	*Education*	*Working*	*Hukou*	*FMS*	*Urban SHI*	*NCMS*
PHI	1.00											
Age	-0.04	1.00										
Gender	0.01	-0.00	1.00									
Chronic diseases	0.00	0.35	0.01	1.00								
Household income	0.06	-0.07	0.01	0.01	1.00							
Household size	-0.05	-0.18	-0.00	-0.10	0.23	1.00						
Education	0.10	-0.40	0.15	-0.10	0.19	-0.03	1.00					
Working	0.03	-0.46	0.16	-0.23	0.14	0.09	0.17	1.00				
Hukou	-0.14	-0.11	-0.01	-0.13	-0.12	0.19	-0.30	0.24	1.00			
FMS	0.22	0.05	0.06	0.06	0.09	-0.08	0.17	-0.02	-0.27	1.00		
Urban SHI	0.02	0.14	0.02	0.13	0.20	-0.14	0.20	-0.13	-0.49	-0.13	1.00	
NCMS	-0.04	0.05	-0.01	-0.02	0.05	0.06	-0.17	0.10	0.46	-0.17	-0.32	1.00

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N=80,745.

Hukou = the rural *hukou*; FMS = government employees' scheme; NCMS = rural SHI schemes.

Computation referred to a user-written programme in Stata to handle the multiply-imputed data (Eddings and Marchenko, 2010).

5.1.2 Fitting the individual-level model

The following set of longitudinal, mixed-effect models has two levels: observations within individual at level one, and individuals at level two. As Table 5.3 shows, Model 1 only includes the time variables, which shows that adjusting the longitudinal relationship between the observations and the individuals, the correlation of the survey year with PHI enrolment dramatically decreased between 2000 and 2004, but started to rise after 2004, in line with the trend in the descriptive chart (Figure 5.1). When counting in age (and squared age, as the literature suggests that the relationship between age and PHI enrolment is quadratic (Liu and Wang, 2012, Zang et al., 2012, Zhu and Yu, 2015, Yuan et al., 2014, Li et al., 2012a)) and gender, in Model 2, the significant time effect still exists, and age shows a negative quadratic relationship with PHI enrolment. Further, adding the chronic diseases variable to Model 3, all previously significant coefficients hold, and the new variable has a positive correlation with PHI enrolment.

In Model 4 (Table 5.3), the effects of household income and the household size are both significant. The former is positively associated with PHI enrolment, while the latter is negatively associated with it. Given the household income, a larger household size means lower income per capita and hence a weaker ability to buy PHI. This is consistent with a large number of previous studies (Liu and Wang, 2012, Zang et al., 2012, Liu et al., 2011b, Xu et al., 2013, Dong and Zhao, 2013, Wang et al., 2015, Zhu and Yu, 2015, Wang, 2011, Wang, 2009, Li et al., 2012a, Zhu and Gui, 2014). It is worth noting that adding the two variables reduces the coefficients of the time variables, especially 2009 and 2011, suggesting that the over-time variation in PHI appears to have been partly offset by rising affluence in the whole population. Additionally, age also shows such an offset effect in Model 2, although the impact is relatively weak.

Model 5 continues to include the variables of education levels, working status and *hukou*, all demonstrating significant effects (Table 5.3). The first two are positively associated with PHI enrolment while the rural *hukou* is negatively associated with it. In addition, adding the new variables reduces the magnitude of the effect of chronic diseases. With reference to the correlation table (Table 5.3), the correlation between having a diagnostic history of chronic diseases and PHI enrolment may be partly explained by the working status and *hukou*. On top of these, overall, step-by-step adding variables hardly reduces the significance levels of old variables (except the significance value of the chronic diseases variable, which reduces from $p \le 0.01$ to $p \le 0.10$).

Finally adding the SHI variable, compared to no SHI, all types of SHI schemes are significantly positively correlated with PHI enrolment (Table 5.3: Model 6). In addition, the result suggests that by comparison the FMS members had the highest association with PHI enrolment (OR = 7.38, 95% CI 6.27 – 8.66), and the rural NCMS members had higher association with PHI enrolment (OR = 5.80, 95% CI 4.87 – 6.91) than urban SHI members (OR = 2.74, 95% CI 2.23 – 3.36).[24] This is inconsistent with the correlation table (Table 5.2), which shows higher PHI prevalence among the urban SHI members than among NCMS members. The possible explanation is that the relatively low prevalence of PHI within the NCMS members could be attributed to some associated individual characteristics, such as being younger, poorer and less educated than their urban counterparts. After controlling for these characteristics, the NCMS membership itself actually provided greater momentum to PHI enrolment than urban SHI schemes.

Moreover, adding the SHI variable does not heavily impact the significance of most other independent variables, but reduces their magnitude because the SHI variable

[24] OR = odds ratio; CI = confidence interval

is more or less correlated to other variables in this model, and thus may partly explain the variation that could have been explained by them. The coefficient of working status becomes insignificant after adding the SHI variable. This could be attributed to the institutions of China's SHI system, where occupation strongly determines which SHI scheme the individual belongs to (Liang and Langenbrunner, 2013) (for details see Section 1.2.1).

In terms of random effects, variance at the individual level gradually reduces from Model 2 to Model 6 (from 1.86 to 0.74), which means that as new independent variables are added step by step, more and more variation at the individual level has been explained by the included variables. The individual-level variance partition coefficients (VPCs)[25] are 0.35, 0.36, 0.36, 0.28, 0.22 and 0.18 from Model 1 to Model 6, respectively, suggesting that the residual variation attributed to unobserved individual characteristics reduces from about 35% to 18% of total variation from Model 1 to Model 6. As VPC starts to drop relatively fast after adding socioeconomic variables and the SHI variable, this suggests that these variables have relatively strong explanatory power of PHI enrolment.

[25] A certain level VPC = variance of this level / sum of variances of all levels. The first level variance in all logistic models is 3.29

Table 5.3 Individual-level mixed-effect models for PHI prevalence

Model	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*
			Fixed effect: coefficient (S.D.)			
Year	Reference = 2000					
2004	-2.07(0.11)***	-2.12(0.11)***	-2.12(0.11)***	-2.22(0.11)***	-2.21(0.11)***	-2.25(0.11)***
2006	-2.06(0.09)***	-2.11(0.10)***	-2.11(0.09)***	-2.25(0.10)***	-2.23(0.10)***	-2.37(0.10)***
2009	-1.80(0.08)***	-1.86(0.08)***	-1.87(0.08)***	-2.18(0.09)***	-2.10(0.09)***	-2.49(0.10)***
2011	-1.65(0.08)***	-1.71(0.08)***	-1.72(0.08)***	-2.06(0.09)***	-1.99(0.08)***	-2.36(0.09)***
Age		0.10(0.01)***	0.10(0.01)***	0.08(0.01)***	0.08(0.01)***	0.06(0.01)***
Age^2		-0.00(0.00)***	-0.00(0.00)***	-0.00(0.00)***	-0.00(0.00)***	-0.00(0.00)***
Gender		0.10(0.06)	0.09(0.06)	0.07(0.06)	-0.04(0.06)	-0.09(0.06)
Chronic diseases			0.31(0.07)***	0.25(0.07)**	0.13(0.07)†	0.11(0.07)
Household income				0.53(0.03)***	0.37(0.03)***	0.28(0.03)***
Household size				-0.26(0.02)***	-0.16(0.02)***	-0.12(0.02)***
Education	Reference = no or primary school					
Middle or tech					0.42(0.07)***	0.28(0.07)***
University					0.86(0.10)***	0.54(0.10)***
Working					0.20(0.07)**	0.06(0.07)
Hukou					-1.22(0.08)***	-1.21(0.09)***
SHI	Reference = no SHI					
FMS						2.00(0.08)***
Urban SHI						1.01(0.10)***
NCMS						1.76(0.09)***

Random effect: variance (S.D.)						
Individual-level	1.80(0.17)***	1.86(0.18)***	1.84(0.18)***	1.26(0.14)***	0.95(0.13)***	0.74(0.13)***
Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,745. Significance values: ᵗp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.						

5.2 Adding the community level

This section continues to model PHI enrolment by adding the community level and aggregate variables. It likewise starts with the descriptive analysis of aggregate-level factors.

5.2.1 Descriptive analysis

The community, or neighbourhood, is the primary sampling unit of the CHNS, where sampled individuals with their households are consistently clustered in the same communities during the five waves of survey[26], as mobility leads to unit non-response. In this study, the community is selected as the top level of the model.

Along with the community level are aggregate-level variables. One is the geography variable, indicating whether the east areas or the inland areas of China the community belongs to. Another is the community type variable, indicating whether it is an urban or rural community. Apart from these, there are three variables acting as the PHI-prevalence-related community development indexes (all are continuous, ranging between 0 and 10), indicating levels of population density, social services and health infrastructure in the community, respectively. The choice and rationales for these variables are elaborated in Section 3.3.2.

The three community development indexes are summarised in the crosstab of geographies and community types (Table 5.4). Most evidently, it is shown that they all tend to be the highest in the urban east and the lowest in the rural inland, except the level of social services, in which communities of the urban inland performed slightly better than their counterparts in the urban east. This suggests that in general the more affluent east and urban areas are also more developed than the inland and rural areas with respect to these indices.

[26] CHNS happened to add new households on a large scale to address attritions in 2000

Table 5.4 Crosstabulation of aggregate variables					
	East		*Inland*		*Total*
	Urban	*Rural*	*Urban*	*Rural*	
Population density	7.40(1.23)	5.95(1.17)	6.64(1.23)	5.30(1.32)	5.99(1.45)
Social services	4.60(3.23)	2.50(2.50)	4.66(3.08)	2.30(1.97)	3.15(2.76)
Health infrastructure	7.16(1.64)	5.47(2.28)	6.63(2.06)	4.76(2.53)	5.62(2.46)

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471 (A few communities have missing values for community development indexes. Because the number is very small and imputing aggregate data with individual data is not appropriate, the missing aggregate data are not imputed).
Two-way ANOVA tests show that difference of the population density index, the social services index and the health infrastructure index are all significant across geographies and community types (for all $p<0.001$).

Furthermore, summarising PHI enrolment and SHI enrolment by the geography variable and the community type variable (Table 5.5), it can be seen that the distribution of PHI tilts towards east and urban areas. The enrolment rate of PHI in the urban east is five times greater than that in the rural inland. The enrolment rates of the FMS and the urban SHI are much higher in urban areas than in rural areas, while the NCMS members are concentrated in rural areas. Additionally, the enrolment rates of all SHI schemes tend to be higher in the east than inland.

Table 5.5 The summary of SHI and PHI prevalence by geographies and community types					
	East		*Inland*		*Total*
	Urban	*Rural*	*Urban*	*Rural*	
PHI	0.10(0.00)	0.07(0.00)	0.08(0.00)	0.02(0.00)	0.05(0.00)
FMS	0.15(0.00)	0.05(0.00)	0.13(0.00)	0.02(0.00)	0.06(0.00)
Urban SHI	0.46(0.01)	0.16(0.00)	0.37(0.00)	0.05(0.00)	0.20(0.00)
NCMS	0.08(0.00)	0.43(0.00)	0.07(0.00)	0.41 (0.00)	0.29(0.00)

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 81,755.
F Tests show that prevalence of PHI, FMS, urban SHI and NCMS are all significantly different across geographies and community (for all $p<0.001$).

5.2.2 Fitting the three-level model

Adding the community level alone, as is shown in Model 7 (Table 5.6), magnitude of the effects of most existing variables in the two-level model reduce after adding the third level. This means that the effects of individual and time variations have been partially attributed to community-level variance. However, adding the third level does not impact the significance and direction of these individual variables, except the positive effect of the working status, which reaches significance again.

Adding the variables of geographies and community types at the second step, the positive effects of eastern and urban communities on individuals' PHI enrolment are both significant (east versus inland: OR = 2.33, 95% CI 1.72 – 3.17; urban versus rural: 2.84, 95% CI 2.05 – 3.94) (Table 5.6: Model 8). This means that for those living in the east and urban areas of China, the odds of being enrolled into PHI were 2.33 and 2.84 times as large as the odds for those living in the inland and rural areas of China being enrolled into PHI, respectively. Corroborating the finding in the literature review (Section 2.3.2) with more sufficient evidence, this suggests that in addition to its well-known distribution in favour of high socioeconomic status, after controlling for individual characteristics, PHI distribution is still in favour of more affluent areas in China, even if SHI schemes generally have better coverage in these areas, too (Meng et al., 2012, Suo et al., 2015, Liang and Langenbrunner, 2013).

Finally, the model includes the three community development indices. The community's health infrastructure level has a significantly positive coefficient (OR = 1.05, 95% CI 1.01 – 1.08). This suggests that better health infrastructure may facilitate the use of health services and hence raise the demand for PHI, to cover the rising costs. The community's social services availability (including health insurance) has a marginally significantly negative correlation with PHI enrolment (OR = 0.98, 95% CI 0.96 – 1.00) (Table 5.6: Model 9). This may be interpreted as meaning that the feeling of having better social security reduces the demand for PHI. The coefficient of the community population density is not significant. After adding these aggregate variables, the coefficients of individual variables almost remain the same, except time effects, which slightly reduce, possibly because the development indices change over time.

In terms of random effects, adding the community level more than halves variance at the individual level from 0.74 to 0.32, suggesting that the individual variance can be explained in part by the community variation. In addition, adding community variables such as geographies, community types and community development indices gradually reduces the community-level random effect, because some of the effect has been explained by these variables. According to Model 9 (Table 5.6), the complete three-level model, the community-level VPC equals 0.19 and the individual-level VPC equals 0.07, which means that finally in the model 19% and 7% of variation in PHI enrolment are attributed to unobserved community-level and individual-level factors, respectively.

Table 5.6 The three-level models on PHI enrolment

Model	*Model 7*	*Model 8*	*Model 9*
Fixed effect: coefficient (S.D.)			
Year	Reference = 2000		
2004	-2.17(0.11)***	-2.16(0.11)***	-2.08(0.11)***
2006	-2.17(0.10)***	-2.16(0.10)***	-2.08(0.11)***
2009	-2.10(0.10)***	-2.09(0.10)***	-2.05(0.10)***
2011	-1.93(0.10)***	-1.91(0.10)***	-1.86(0.11)***
Age	0.05(0.01)***	0.05(0.01)***	0.05(0.01)***
Age^2	-5.93e-4(0.00)***	-5.88e-4(0.00)***	-5.85e-4(0.00)***
Gender	-0.06(0.06)	-0.06(0.06)	-0.06(0.06)
Chronic diseases	0.06(0.07)	0.06(0.07)	0.06(0.07)
Household income	0.21(0.03)***	0.20(0.03)***	0.20(0.03)***
Household size	-0.09(0.02)**	-0.09(0.02)**	-0.08(0.02)**
Education	Reference = no or primary school		
Middle or tech	0.24(0.07)**	0.22(0.07)**	0.22(0.07)**
University	0.43(0.10)***	0.40(0.10)***	0.40(0.10)***

Working	0.18(0.07)**	0.19(0.07)**	0.19(0.07)**
Hukou	-0.61(0.12)***	-0.52(0.12)***	-0.51(0.12)***
SHI	Reference = no SHI		
FMS	1.82(0.08)***	1.81(0.08)***	1.81(0.08)***
Urban SHI	0.61(0.11)***	0.59(0.11)***	0.60(0.11)***
NCMS	1.29(0.09)***	1.29(0.09)***	1.30(0.09)***
Aggregate variables			
East		0.84(0.15)***	0.85(0.16)***
Urban		1.04(0.17)***	1.05(0.18)***
Population density			-0.04(0.05)
Social service			-0.02(0.01)[ǂ]
Health infrastructure			0.05(0.02)**
Random effect: variance (S.D.)			
Community-level	1.20(0.19)***	0.88(0.13)***	0.87(0.13)***
Individual-level	0.32(0.13)*	0.32(0.13)*	0.32(0.13)*
Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471. Significance values: [ǂ]p≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.			

5.3 Disaggregation

To examine spatial inequality, the same three-level model is fitted based on the four subpopulations of the urban east, the rural east, the urban inland and the rural inland, respectively (Table 5.7: Model 9a – 9d). In general, the profiles of significance and direction of coefficients of the four models are alike, suggesting that these determinants basically have similar effects on PHI enrolment across different areas in China.

Notwithstanding the general similarity, a few differences emerge. First, magnitude of income and education coefficients is visibly greater in the poorest rural inland areas than in other areas, which possibly suggests that PHI's distribution in poorer areas is more likely to be determined by individual socioeconomic factors than that in other areas, echoing a previous finding (Suo et al., 2015). Second, since an urban resident with a rural *hukou* typically indicates a rural-to-urban immigrant, the insignificant effect of the rural *hukou* in urban areas (Table 5.7: Model 9a and 9c) contradicts the findings of two previously reviewed studies that suggest higher prevalence of PHI among urban immigrants (see Section 2.3.2). The possible explanation is that the rural *hukou* highly correlates to the NCMS membership in urban areas (Cramer's V = 0.44, $p < 0.00$), which has been taken into account in the models already. In the two urban models, the greater positive coefficients of the NCMS, relative to the urban SHI, suggest that the higher prevalence of PHI among immigrants relative to locals still exists.

By contrast, in rural areas, the rural *hukou* has a significantly negative effect (Table 5.7: Model 9b and 9d). A possible explanation is that the expansion of cities causes some urban *hukou* holders to live in suburbs that have been categorised as rural areas, who are more likely to be enrolled in PHI than real peasants, those living in rural areas with the rural *hukou*. Actually, in rural areas, the correlation between the urban *hukou* and the urban SHI membership (Cramer's V = 0.48, $p < 0.00$) is much more positive than that between the urban *hukou* and the NCMS membership (Cramer's V = -0.28, $p < 0.00$), suggesting that these rurally-living urban *hukou* holders tend to work in urban areas, join the urban SHI, and enjoy urban medical benefits.

Looking at SHI schemes, the NCMS's positive association with PHI enrolment is generally stronger than that of the urban SHI, especially in the two urban areas (in urban east, NCMS: OR = 7.07, 95% CI 4.34 – 11.55, urban SHI: OR = 2.15, 95% CI 1.38 – 3.35; in urban inland, NCMS: OR = 3.91, 95% CI 2.52 – 6.08, urban SHI: OR = 2.58, 95% CI 2.00 – 3.34), as aforementioned. Because it is known that generosity of the NCMS reduces greatly outside of rural areas (Yip et al., 2012), the urban NCMS members, due to migration and the fact that they do not work in formal sectors (which offer urban SHI to employees), may have a greater demand for PHI to compensate for the shortage of insurance coverage.

In terms of community-level variables, the population density only has a significant positive association with PHI enrolment in the rural inland (Table 5.7: Model 9d). This suggests that in the poorest and most underpopulated regions, the population density matters for accessibility of PHI, due possibly to commercial insurers' marketing strategies biased against remote rural places. The negative effect of the social service index is only significant in the rural east (Table 5.7: Model 9b), implying that only social services in the rural east are effective enough to reduce people's feelings of insecurity, so as to reduce PHI prevalence. Moreover, the effect of the health infrastructure index is significant (or marginally significant) in all three regions except the rural inland, which suggests that health infrastructure in the rural inland may be too poor in quality or (hence) too under-resourced to influence the residents' PHI enrolment.

Regarding random effects (Table 5.7), for most subpopulations, the unobserved variation in PHI enrolment is attributable more to community variance than individual variance, except the rural inland population, where the variation is attributable more to individual variance (community-level VPC = 0.146; individual-level VPC = 0.155). This echoes the fixed effects: the effects of individual variables in determining PHI enrolment are more substantial in the rural inland than those in the other three. Additionally, the two urban subpopulations appear to have much smaller variances at both community and individual levels than those of two rural subpopulations. Altogether, these again suggest that, from the perspective of unobserved variation, the inequality of PHI prevalence in rural areas seems greater than in urban areas. The inequality is more likely to come from community variation in the rural east, but from individual variation in the rural inland.

Table 5.7 The models on PHI enrolment based on subpopulations

	Urban east	*Rural east*	*Urban inland*	*Rural inland*
Model	*Model 9a*	*Model 9b*	*Model 9c*	*Model 9d*
Fixed effect: coefficient (S.D.)				

Year	Reference = 2000			
2004	-2.48(0.21)***	-1.91(0.17)***	-2.19(0.19)***	-2.04(0.26)***
2006	-3.08(0.29)***	-1.47(0.15)***	-2.34(0.20)***	-1.53(0.26)***
2009	-2.60(0.22)***	-1.55(0.17)***	-2.47(0.18)***	-1.64(0.29)***
2011	-2.87(0.27)***	-0.79(0.16)***	-2.55(0.20)***	-1.64(0.28)***
Age	0.05(0.02)*	0.04(0.02)*	0.04(0.02)**	0.05(0.03)*
Age^2	-6.23e-4(0.00)**	-5.65e-4(0.00)**	-4.97e-4(0.00)**	-6.88e-4(0.00)*
Gender	0.06(0.12)	-0.04(0.09)	-0.12(0.10)	-0.09(0.13)
Chronic diseases	0.01(0.14)	0.07(0.12)	0.04(0.12)	0.08(0.18)
Household income	0.21(0.06)***	0.18(0.06)**	0.19(0.05)**	0.29(0.07)***
Household size	-0.10(0.05)ǂ	-0.10(0.03)**	-0.07(0.04)ǂ	-0.09(0.04)*
Education	Reference = no or primary school			
Middle or tech	0.07(0.18)	0.16(0.10)	0.18(0.14)	0.38(0.15)*
University	0.16(0.24)	0.29(0.23)	0.45(0.17)*	0.54(0.34)
Working	0.19(0.14)	0.34(0.11)**	0.24(0.10)*	-0.08(0.15)
Hukou	-0.18(0.27)	-0.56(0.14)***	-0.10(0.20)	-0.67(0.20)**
SHI	Reference = no SHI			
FMS	1.95(0.17)***	1.52(0.16)***	1.77(0.12)***	2.41(0.24)***
Urban SHI	0.76(0.22)**	-0.46(0.18)*	0.95(0.13)***	1.40(0.28)***
NCMS	1.96(0.25)***	0.69(0.14)***	1.36(0.22)***	0.96(0.24)***
Aggregate variables				
Population	0.09(0.10)	-0.16(0.10)ǂ	-0.04(0.08)	0.18(0.07)**
Social services	0.02(0.03)	-0.06(0.02)*	0.01(0.02)	0.04(0.03)
Health infrastructure	0.08(0.05)ǂ	0.08(0.03)*	0.08(0.04)*	9.76e-4(0.03)
Random effect: variance (S.D.)				
Community-level	0.59(0.21)**	1.72(0.46)***	0.52(0.18)**	0.69(0.18)***
Individual-level	0.29(0.24)	0.38(0.15)*	0.21(0.16)	0.73(0.30)*
Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471 (Urban east: n=9265; Rural east: n=17210; Urban inland: n=19400; Rural inland: n=34870). Significance values: ǂp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.				

5.4 Changing relationships with SHI memberships

These longitudinal models above estimate average effects across the whole period. However, if the relationship between an independent variable and the dependent variable experiences a significant change during the study period, the validity of the corresponding estimates should be questioned. Given the importance of SHI in this study, it is particularly worth investigating whether the relationships between SHI and PHI significantly changed as health reforms proceeded.

5.4.1 Over-time descriptive analysis

Before focusing on SHI, I descriptively explore the four typical determinants of PHI enrolment identified previously (Figure 5.2), i.e. household income (inflated to 2011 CPI), *hukou,* the education level and the place of residence. According to the estimates of Model 9 (Table 5.6), compared to those without PHI, PHI enrolees tended to be wealthier, more educated, with an urban *hukou*, and living in east and urban areas. The following charts, which describe the temporal variations in relationships between these determinants and PHI enrolment, are all consistent with the model estimates. Although some differences between PHI enrolees and non-enrolees were narrower, such as in education levels, *hukou* status and the urban-rural dichotomy, PHI enrolees still maintained these characteristics (or advantages) against those without PHI in each study year. This suggests that relationships between these determinants and PHI enrolment are generally time-invariant.

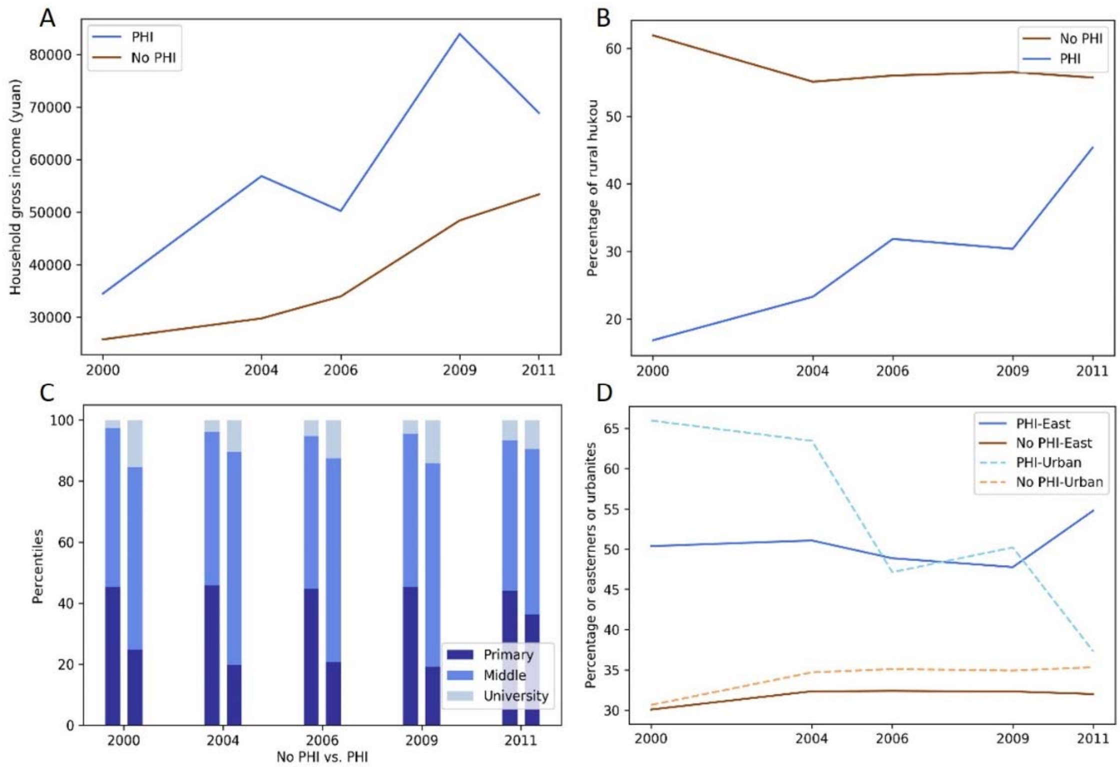

Figure 5.2: Compositions of PHI enrolees and non-enrolees during 2000 – 2011: household gross income (A), *hukou* (B), the education level (C) and residential places (D). Data source: CHNS; N = 81,745.

In terms of SHI, as Table 5.8 shows below, in 2000 the PH-enrolment rates among SHI enrolees, regardless of schemes, were much higher than the rate among those without SHI. However, this disparity dramatically reduced between 2000 and 2004, due to a great fall in these rates among SHI enrolees. Since then, as the PHI-enrolment rate increased faster among those without SHI than among SHI enrolees, the relationship between SHI and PHI appeared to be reversed; in 2011, the PHI-enrolment rate of those without SHI has been much higher than those of SHI enrolees.

Table 5.8 PHI enrolment rates among SHI scheme enrolees

SHI type	*2000*	*2004*	*2006*	*2009*	*2011*	*Total*	*P value*
None	0.01(0.00)	0.02(0.00)	0.02(0.00)	0.09(0.01)	0.16(0.02)	0.03(0.00)	<0.001
FMS	0.63(0.01)	0.04(0.01)	0.04(0.01)	0.05(0.01)	0.02(0.01)	0.24(0.01)	<0.001
Urban SHI	0.47(0.02)	0.03(0.01)	0.03(0.01)	0.03(0.00)	0.03(0.00)	0.06(0.00)	<0.001

NCMS	0.53(0.02)	0.02(0.01)	0.02(0.00)	0.02(0.00)	0.02(0.00)	0.04(0.00)	<0.001
Total	0.13(0.00)	0.02(0.00)	0.03(0.00)	0.03(0.00)	0.04(0.00)	0.05(0.00)	
P value	<0.001	0.16	0.05	<0.001	<0.001	N/A	
Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 81,755. Those in parentheses are standard errors; F tests are applied to difference among years for each SHI type and difference among SHI types for each year.							

Consequently, the descriptive analysis indicates that the model estimation of SHI's effects may be at risk of losing too much information by averaging these effects across the period 2000-2011. In particular, the results of the previous models (Model 9 and backwards), which show a positive relationship between SHI membership and PHI enrolment compared to no SHI, may be predominantly influenced by the 2000 data. This calls for special attention paid to the period between 2000 and 2004.

5.4.2 The change between 2000 and the years after 2000

This section sets out to examine what happened to SHI's effects between 2000 and other years in the survey by adding the interaction between the SHI variable and an indicator of time transition.

Table 5.9 below shows that there was indeed a significant change in the effect of SHI on PHI enrolment between 2000 and the years after 2000. In 2000, the relationships between SHI schemes and PHI were all significantly positive (FMS: OR = 109.77, 95% CI 80.15 – 150.34; urban SHI: OR = 51.27, 95% CI 35.86 – 73.30; NCMS: OR = 54.10, 95% CI 39.03 – 75.00); It means that, in 2000 for enrolees of FMS, urban SHI and NCMS, the odds of being enrolled into PHI were 109.77, 51.27 and 54.10 times as large as the odds for SHI non-enrolees being enrolled into PHI, respectively.

However, the negative interactions with years after 2000 were so strong that they reverse the effects in magnitude of all SHI schemes after combining the main effects of SHI schemes and the corresponding interactions (from 2004 to 2011) (FMS: OR = 0.40, 95% CI 0.29 – 0.55; urban SHI: OR = 0.34, 95% CI 0.28 – 0.42; NCMS: OR =

0.72, 95% CI 0.59 – 0.88). This suggests that from 2004 to 2011, for enrolees of FMS, urban SHI and NCMS, the odds of being enrolled into PHI sharply reduced to 0.40, 0.34 and 0.72 times as large as the odds for SHI non-enrolees being enrolled into PHI, respectively. The trend prevails across the entire population and the four subpopulations. The Chow tests confirm that the coefficients of SHI schemes significantly differ between the two time periods for all populations.[27] Importantly, the new finding demonstrates that the results of the previous models (Table 5.6 and 5.7) are so predominantly influenced by the 2000 data that they mask the information from later years.

Table 5.9 SHI effect change between 2000 and later years

	Total	*Urban east*	*Rural east*	*Urban inland*	*Rural inland*
Model	*Model 10*	*Model 10a*	*Model 10b*	*Model 10c*	*Model 10d*
			Coefficient (S.D.)		
Post-2000‡	1.02(0.13)***	1.32(0.41)**	0.99(0.19)***	1.00(0.24)***	0.78(0.26)**
SHI	Reference = no SHI				
FMS	4.70(0.00)***	5.24(0.45)***	4.01(0.26)***	4.74(0.25)***	5.37(0.38)***
Urban SHI	3.94(0.00)***	4.25(0.43)***	2.52(0.35)***	4.17(0.27)***	5.15(0.49)***
NCMS	3.99(0.00)***	5.95(0.62)***	2.93(0.23)***	4.57(0.49)***	6.70(0.50)***
Post-2000×FMS	-5.62(0.24)***	-6.17(0.59)***	-4.73(0.37)***	-5.86(0.37)***	-6.13(0.66)***
Post-2000×Urban SHI	-5.02(0.20)***	-5.55(0.50)***	-3.89(0.39)***	-5.25(0.33)***	-5.32(0.54)***
Post-2000×NCMS	-4.32(0.19)***	-6.92(0.75)***	-3.34(0.26)***	-5.33(0.58)***	-7.14(0.55)***

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471 (Urban east: n=9265; Rural east: n=17210; Urban inland: n=19400; Rural inland: n=34870).
Significance values: ɫp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.
Adjusted for demographic, socioeconomic and aggregate variables like those in Model 9.
The Chow tests shows that there is a significant change in the coefficients of SHI schemes between the two periods, for the whole population and all subpopulations (p<0.001 for all populations).
‡ The 2004, 2006, 2009 and 2011 years.

[27] The Chow test tests the main effect of the time transition and their interactions with SHI schemes being equal to 0.

To seek explanations for this change from related policy impacts, the most visible consequence of these policies is the expansion of the urban SHI and the NCMS, driving the total SHI coverage from around 20% in 2000 to more than 90% in 2011, according to the CHNS data (Figure 5.3). The expansion of SHI, especially the NCMS, enrolled more people of lower socioeconomic status, narrowing the compositional difference between SHI enrolees and non-enrolees (this will be further analysed later). As PHI enrolment is strongly associated with socioeconomic factors, the compositional change of SHI enrolees could result in changed relationships between SHI and PHI in the models.

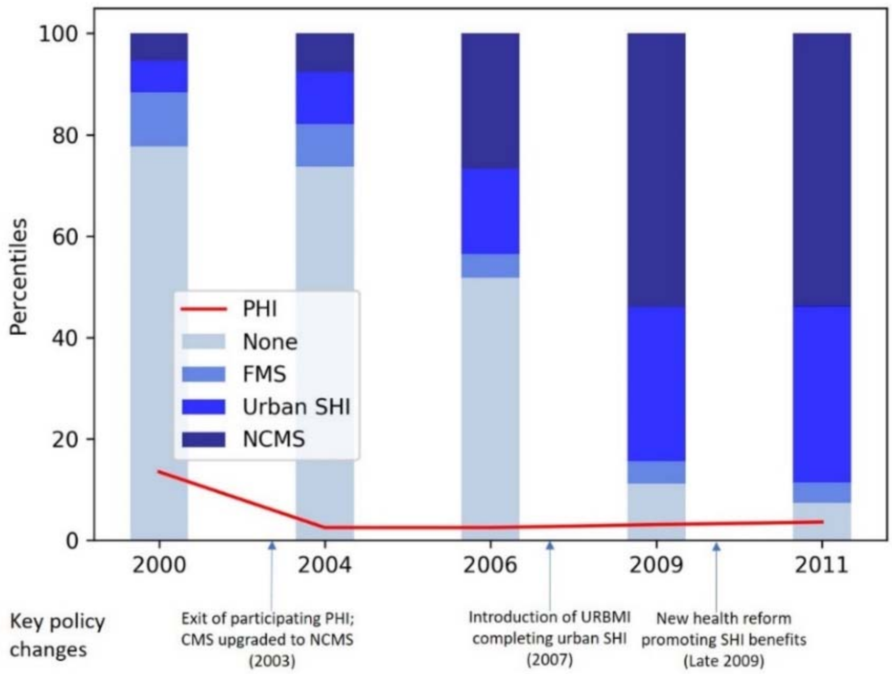

Figure 5.3: Enrolment rates of SHI schemes and PHI in the whole population and related policy changes between 2000 and 2011.

Additionally, what the CHNS data cannot show is the gradually increasing SHI benefits, well-documented in the literature (Yip et al., 2012, Meng et al., 2012). Taking the NCMS as an example, from 2003 to 2010 the government subsidy per person rose from ¥20 to ¥120 (¥1≈ £0.11 or \$0.14) (Dai et al., 2011), and doubled to ¥240 by

2012 (Liang and Langenbrunner, 2013). Theoretically, the generosity promotion could reduce the demand for PHI among SHI enrolees, compared to non-enrolees, due to the increasing overlap in coverage between SHI and PHI.

Looking to the concurrence of the policy on PHI. Coincidentally, in 2003, the China Insurance Regulatory Commission published a regulation that banned a contemporarily popular type of PHI – participating PHI, a combination of health insurance and investment that not only paid indemnity for critical illnesses but also regularly yielded dividends, possibly in order to attract customers (Duan, 2008). Banning this type of PHI has plausibly contributed to the reduced prevalence of PHI between 2000 and 2004. It might also have especially influenced SHI enrolees' demand for PHI, because at that time SHI enrolees, who were at higher socioeconomic status (see Figure 5.4 in Section 5.4.4), might have been more interested in these investment-like PHI products than those without SHI.

5.4.3 Excluding the 2000 data

The descriptive analysis above (Table 5.8) has just shown that information from 2000 about the relationships between SHI membership and PHI enrolment appears so different from that from other years. Because a multitude of PHI enrolees are distributed in 2000 (Figure 5.3), information from the year 2000 substantially interferes with the related analysis of data from other years, when they are modelled together. To avoid this problem, this section sets out to exclude the 2000 data and fit the models based on the remaining data.

Fitting the basic three-level model like Model 9 based on data excluding the year 2000 (Table 5.10), as a result, exactly opposite to those from the whole 2000 – 2011 data, the effects of all SHI schemes become significantly negative, compared to no SHI (based on the whole population, FMS: OR = 0.29, 95% CI 0.20 – 0.44; urban SHI: OR

= 0.17, 95% CI 0.12 – 0.23; NCMS: OR = 0.31, 95% CI 0.23 – 0.41).[28] It suggests that, contrary to what occurred in 2000, between 2004 and 2011 the correlations between enrolment into PHI and enrolment into all SHI schemes were significantly lower than those without SHI; for enrolees of FMS, urban SHI and NCMS, the odds of being enrolled into PHI were 0.29, 0.17 and 0.31 times as large as the odds for SHI non-enrolees being enrolled into PHI, respectively. Although the magnitude increases after excluding 2000 data compared to the interaction models with the whole data (Table 5.9), the results are basically consistent.

Additionally, excluding the 2000 data has little impact on the relations between SHI schemes and between regions. For example, the odds ratios of the FMS and the NCMS are still higher than the urban SHI. The NCMS also has the highest effects among SHI schemes in the two urban subpopulations, still suggesting that the NCMS enrolees were more associated with PHI enrolment than other SHI enrolees in urban areas, due possibly to the reduced benefits of the NCMS in urban areas as aforementioned (Liang and Langenbrunner, 2013).

Table 5.10 The models based on data excluding the year 2000

	Total	*Urban east*	*Rural east*	*Urban inland*	*Rural inland*
	Model 11	*Model 11a*	*Model 11b*	*Model 11c*	*Model 11d*
	Coefficient (S.D.)				
SHI	Reference = no SHI				
FMS	-1.23(0.20)***	-1.41(0.36)***	-0.95(0.30)**	-1.36(0.30)***	-1.35(0.64)*
Urban SHI	-1.79(0.15)***	-1.85(0.27)***	-2.28(0.24)***	-1.62(0.23)***	-1.24(0.34)***
NCMS	-1.18(0.14)***	-1.18(0.48)*	-1.40(0.20)***	-1.20(0.34)***	-1.63(0.28)***

Data source: CHNS (2004, 2006, 2009, 2011); N = 64,596.
Significance values: ⁱp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.
Only the coefficients of SHI are presented; for the full model information, see Appendix C.

[28] As expected, most other coefficients are similar between the corresponding models including and excluding the 2000 data, suggesting that the model specification is basically robust, while the changes in SHI's effects are exceptional (for details see Appendix C).

5.4.4 The compositional change of SHI enrolees

Notwithstanding the background factors that have been controlled for in the models, compositional influence still matters, given non-experimental data. As SHI non-enrolees gradually reduced from a major part of the population to a minority (Figure 5.3), their composition might experience some great transitions. and it is thus interesting to scrutinise the compositional change of SHI enrolees relative to SHI non-enrolees, which would possibly provide an insight into the findings.

First, the two typical socioeconomic factors and determinants of PHI's prevalence, household income and the education level (Figure 5.5), are examined. In general, SHI enrolees were more socioeconomically advantaged than SHI non-enrolees in most periods, but this disparity has been greatly reduced after 2006. In terms of household income (the left chart), the household earnings of SHI non-enrolees were on average only about two-thirds of the earnings of SHI enrolees' households from 2000 to 2004, while since 2006 the former quickly caught up, to around 90% of the latter from 2009 to 2011. In terms of their education levels (the right chart), from 2000 to 2006, SHI non-enrolees had a higher proportion of the least educated (primary school or none), and a lower proportion of the most educated (university or higher), than SHI enrolees. However, since 2009, the educational gap between SHI enrolees and SHI non-enrolees has largely diminished. In 2011, SHI enrolment even leant towards the least educated.

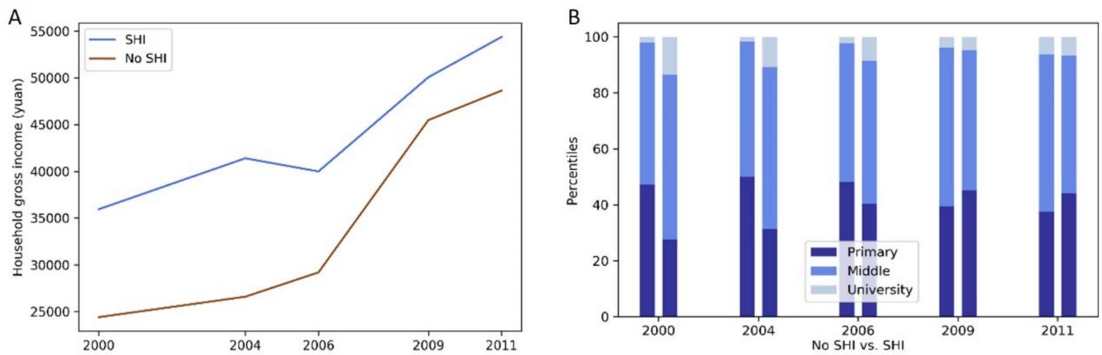

Figure 5.4: Socioeconomic compositions of SHI enrolees and non-enrolees during 2000 – 2011: household income (A); the education level (B). Data source: CHNS; N = 81,745.

Second, geographic difference and difference between the two *hukou* types are examined (Figure 5.6). From 2000 to 2004, the percentages of SHI enrolees were higher among east and urban populations than inland and rural populations (the left chart). Between 2004 and 2009, the SHI enrolment rates in two rural populations caught up and finally exceeded those in the urban populations. Between 2009 and 2011, the varied SHI coverage rates converged, but were still slightly higher in rural populations than in urban populations. Additionally, the rural-*hukou* holders, once predominant among SHI non-enrolees and scarce among SHI enrolees (the right chart), have become the main body of SHI enrolees and only accounted for a small part of SHI non-enrolees after 2006.

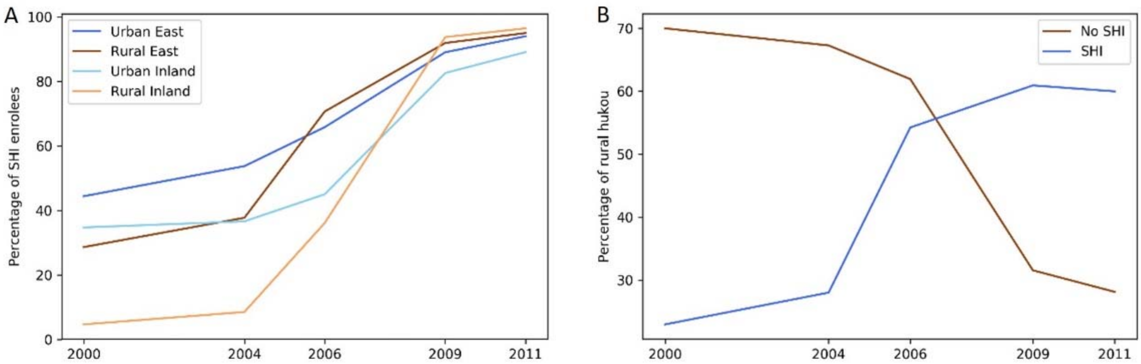

Figure 5.5: SHI enrolment distribution among regions (A) and between *hukou* types (B) during 2000 – 2011. Data source: CHNS; N = 81,745.

In sum, between 2000 and 2011, there is a clear tendency for the SHI coverage to become more equal among socioeconomic strata and spatially. Typical SHI non-enrolees, in the earlier time of this period, were poorer, lower educated, living in rural and inland area, and more likely to be rurally registered in *hukou*, compared to SHI enrolees. At the end of this period, these distinctions have been blurred, except *hukou* where SHI non-enrolees have been even more likely to be the advantaged urban *hukou* holders. These changes demonstrate that the SHI system, as a whole, has been more and more universal and equal. By comparison, this trend is much less likely for PHI, as has been shown before (Figure 5.2).

This tendency towards more identical compositions of SHI enrolees and non-enrolees, and a higher percentage of urban *hukou* holders among SHI non-enrolees, has certainly underpinned the increased likelihood of SHI non-enrolees enrolling in PHI after 2000, as the previous models found. This has been because of the steady positive correlations between PHI enrolment and household income, education level, living in east and urban areas, and the urban *hukou*.

Conclusion

Overall, in China, the prevalence of PHI, after a fall between 2000 and 2004, has been gradually increasing, but very slowly. Individuals with higher socioeconomic status, represented by a greater household income, a smaller household size, being more educated and being registered in the urban *hukou*, were significantly associated with higher likelihoods of PHI enrolment. At the aggregate level, east and urban areas, and the level of community health infrastructure, were significantly associated with a higher PHI prevalence.

The independent variables' effects on PHI enrolment are mostly consistent across regions. However, some spatial differences exist. The positive effects of household income and the education level are relatively strong in the rural inland, suggesting socioeconomic status's greater association with PHI enrolment in the poorer areas. The negative effect of the rural *hukou* only existed in rural areas, while in urban areas the effect was likely to be offset by the rural *hukou*'s correlation with the NCMS membership (typically for immigrants), whose positive effect was relatively strong in urban areas. At the community level, the population density was only positive in the rural inland, implying commercial insurers' prudence in the poor areas. Contrarily, the health infrastructure level was positive in all but the rural inland, due possibly to the very poor quality of health infrastructure in the rural inland.

SHI schemes' effects on PHI enrolment changed between 2000 and 2004. The correlations of PHI enrolment with SHI memberships were higher than that with those without SHI in 2000. After 2000 (2004 – 2011), the prevalent trend was for the correlations of PHI enrolment with SHI enrolees to be reversed, so that it was lower than that of SHI non-enrolees. This change may be explained by the combination of the exit of a contemporarily popular type of PHI in 2003, an increasing number of NCMS enrolees of low socioeconomic status, the overall generosity promotion of SHI, and the compositional transition, which eliminated SHI non-enrolees' socioeconomic and regional disadvantages against SHI enrolees.

Chapter Six: The Effect of PHI on Access to Healthcare

This chapter focuses on examining the effect of private health insurance (PHI) on access to healthcare in China, where PHI can be complementary or supplementary to fill SHI's inadequacies, while substitutive PHI plans are also available for those uncovered by SHI (Luo et al., 2016). Using the 2000, 2004, 2006, 2009 and 2011 data of the China Health and Nutrition Survey (CHNS), as operationalised in the methods chapter (Section 3.1.2 and 3.5.2), the generic utilisation of formal healthcare (whether the individual was treated by a health professional, regardless of outpatient care or inpatient care) has been used as the indicator of access to healthcare.

In the literature review, most of previous related studies examined the effect of PHI on the utilisation of either inpatient care (Li et al., 2016, Jiao, 2015, Zang et al., 2012) or outpatient care (Yang, 2013, Qin et al., 2014, Yao et al., 2012, Zang et al., 2012, Zhu et al., 2008), and some found PHI's positive correlation with the former. However, in practice, using inpatient care usually follows outpatient care, and the choice may be decided by doctors and distorted by the moral hazard. By contrast, generic utilisation may be more indicative of individuals' primary healthcare-seeking behaviour driven by needs, but related studies on this give mixed results (Chai, 2013, You and Kobayashi, 2011, Jiao, 2015, Lam and Johnston, 2012). Evidence on the effect of dual insurance (SHI and PHI) on access to healthcare are also inadequate and ambiguous (Lam and Johnston, 2012, Chai, 2013, Wang, 2012). Additionally, the inequities in healthcare access related to PHI, such as unequal effects of PHI on healthcare utilisation among different populations and the impact of PHI at aggregate-level utilisation, has been under-researched.

Following basic descriptive analyses, the first two sections of this chapter develop step by step the individual-level mixed-effect models that handle the longitudinal data, and then the three-level models with the community level. Based on the final three-level model, from the third section until the end, the study populations are disaggregated for further investigations that highlight spatial inequalities. After a brief examination of the temporal variation of the effects of health insurance schemes in section four, the research proceeds to examine PHI's and SHI's effects, and their interaction, on utilisation under different levels of personal need. Finally, it investigates PHI's and SHI's contextual impacts on communities' average utilisation.

6.1 The individual-level model

The first section starts with the descriptive analysis of individual-level model variables, and then fits the model for healthcare utilisation. Like the last chapter, the longitudinal structure of the data is dealt with at first by the two-level mixed-effect model, where observations are nested within the individuals. Addition of independent variables proceeds step by step, starting with year dummies and demographic variables, then need variables, socioeconomic variables and finally health insurance variables.

6.1.1 Descriptive analysis

The dependent variable in this chapter is whether the individual had used formal healthcare in the past four weeks before the survey, regardless of outpatient or inpatient care. An individual's enrolment into PHI, the dependent variable in the last chapter, is instead included in the model as a key independent variable. Moreover, the variable of health status, i.e. whether the individual was self-reportedly ill or injured in the past four weeks of this survey – which should not influence the status of PHI enrolment and hence is excluded from the models for PHI prevalence – is included as an independent variable in the models for utilisation, indicating the level of personal need for healthcare. Except these above, most variables included in the models remain the same as previously (see Table 5.1). The summary of these new variables is presented in Table 6.1.

Table 6.1 Overview of newly-added model variables			
Variable	*Description*	*Mean(S.D.)*	*Min/Max*
Dependent variable			
Healthcare utilisation	Whether used formal healthcare in past four weeks	0.13(0.50)	0/1
Independent variable			
Health status (need level)	Whether was (self-reportedly) ill or injured in past four weeks	0.14(0.52)	0/1
PHI enrolment	Whether is covered by private health insurance	0.05(0.31)	0/1
Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 81,755.			

Exploring correlations with demographic and socioeconomic variables (Table 6.2), healthcare utilisation is highly correlated with health status (r = 0.68) and moderately correlated with the diagnostic history of chronic diseases (r = 0.22) and age (r = 0.23), respectively. Since these variables typically indicate needs, it suggests that needs appear to play an important role in determining utilisation. In terms of socioeconomic factors, the utilisation appears to have very weak correlations with household income (r =-0.03), the household size (r = -0.02) and hukou (r = -0.02). The moderate negative correlations with the education level (r = -0.11) and working status (r = -0.15) may in part derive from their close relationships with age and health, because individuals who are better educated and working tend to be younger and healthier than those poorer educated and not working. The correlations between the utilisation and health insurance schemes are very weak as well (FMS: r = 0.01; urban SHI: r = 0.03; NCMS: r = 0.04; PHI: r = -0.01), which could be influenced by the correlations between enrolment into a health insurance scheme and other variables.

Table 6.2 Correlations of healthcare utilisation and individual independent variables

	Utilisation	*Age*	*Gender*	*Chronic disease*	*Health status*	*Household income*	*Household Size*	*Education*	*Working*	*Hukou*	*FMS*	*Urban SHI*	*NCMS*	*PHI*
Utilisation	1.00													
Age	0.23	1.00												
Gender	-0.04	-0.00	1.00											
Chronic disease	0.22	0.35	0.01	1.00										
Health status	0.68	0.23	-0.04	0.25	1.00									
Household income	-0.03	-0.07	0.01	0.01	-0.03	1.00								
Household Size	-0.02	-0.18	-0.00	-0.10	-0.04	0.23	1.00							
Education	-0.11	-0.40	0.15	-0.10	-0.10	0.19	-0.03	1.00						
Working	-0.15	-0.46	0.16	-0.23	-0.16	0.14	0.09	0.17	1.00					
Hukou	-0.02	-0.11	-0.01	-0.13	-0.13	-0.12	0.19	-0.30	0.24	1.00				
FMS	0.01	0.05	0.06	0.06	0.02	0.09	-0.08	0.17	-0.02	-0.27	1.00			
Urban SHI	0.03	0.14	0.02	0.13	0.05	0.20	-0.14	0.20	-0.13	-0.49	-0.13	1.00		
NCMS	0.04	0.05	0.01	-0.02	0.01	0.05	0.06	-0.17	0.10	0.46	-0.17	-0.32	1.00	
PHI	-0.01	-0.04	0.01	0.00	0.00	0.06	-0.05	0.10	0.03	-0.14	0.22	0.02	-0.04	1.00

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N=80,745.

Hukou = the rural *hukou*; FMS = government employees' scheme; NCMS = rural SHI schemes.

Computation referred to a user-written programme in Stata to handle the multiply-imputed data (Eddings and Marchenko, 2010).

Descriptively presenting the utilisation (the percentage of formal healthcare users) over time, along with the prevalence of general SHI and PHI (Figure 6.1), we can see that the utilisation rapidly increased between 2000 and 2004, in line with the increase in SHI's prevalence, but contradicting the drop in PHI's prevalence. Afterwards, the utilisation rate kept stable, while SHI apparently accelerated its expansion rate. In addition, it is worth mentioning the steady increase in the average age of this longitudinal data, which should contribute partly to the utilisation variation.

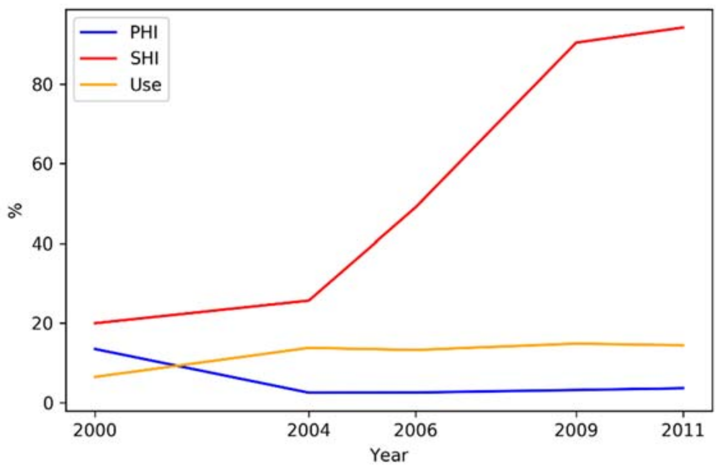

Figure 6.1: Percentages of healthcare users and percentages of PHI enrolees and general SHI enrolees in the study population over time. Data source: CHNS; N = 81,755.

6.1.2 Fitting the individual-level model

The modelling starts with the random-effect model with only a series of year dummies as independent variables (Table 6.3: Model 1). Adjusting the longitudinal relationship between the observations and the individuals, a significant increase in the utilisation of healthcare was associated with years after 2000, and it then became relatively stable between 2004 and 2011, consistent with the descriptive result. The inclusion of age and gender remarkably reduces the effect of time (Table 6.3: Model 2).

However, further including chronic diseases and health status cuts the effect of age by half and slightly reduces the negative effect of gender (Table 6.3: Model 3). It suggests that a considerable part of over-time variation in the utilisation can be explained by a change in the need for healthcare. Remarkably, the variable of health status has a very strong association with the utilisation (Model 3), which accords with the outcome from the crosstabs of the descriptive analysis (Table 6.2).

Afterwards, socioeconomic variables are added in two steps. First, the household income and the household size have opposite effects on the utilisation. The household income is negatively correlated with the utilisation, while the household size is positively correlated with the utilisation (Table 6.3: Model 4), just opposite to their correlations with household affluence and PHI enrolment. Second, adding education, working status and *hukou*, whose effects are all significant, the education level and employment are seen to be negatively correlated with the utilisation of healthcare, and the rural hukou is positively correlated (Table 6.3: Model 5).

An interesting finding is that these above indicating high socioeconomic status are all negatively associated with the utilisation. Apart from health insurance variables and spatial variables which have not been included, a possible explanation is that those with higher socioeconomic status tend to be healthier and hence use less healthcare than those with lower socioeconomic status, given needs' dominant influence on utilisation. Additionally, after counting education, employment and *hukou*, the household income loses significance and the effect of the household size reduces, suggesting close associations between these socioeconomic variables. However, the inclusion of socioeconomic variables has little impact on the coefficients of need variables, suggesting that needs are independent from socioeconomic factors in determining the utilisation of healthcare.

The health insurance variables are finally added. Starting with SHI, except the urban SHI scheme, the government's Free Medical Scheme (FMS) and the rural SHI scheme (NCMS) have significant positive correlations with the utilisation of healthcare (FMS: OR = 1.30, 95% CI 1.08 – 1.56; urban SHI: OR = 1.04, 95% CI 0.89 – 1.21; NCMS: OR = 1.18, 95% CI 1.03 – 1.35) (Table 6.3: Model 6). Adding the SHI variable does not substantially affect most existing independent variables except the household income, which regains significance. By contrast, PHI does not have a significant correlation with the utilisation (OR = 1.11, 95% CI 0.86 – 1.41), and its inclusion hardly affects the coefficients of the other variables (Table 6.3: Model 7).

Looking at random effects, the individual-level variance reduces significantly (from 1.52 to 0.65) as time and need variables are added. As a result, variance partition coefficients (VPCs) drop (from 0.32 to 0.16), which means that the residual variation in healthcare utilisation that is attributed to unobserved between-individual characteristics reduces from 32% to 16%. By comparison, the inclusion of socioeconomic variables as well as health insurance variables together merely reduces the variance by a further 0.06, contributing to a 1% of decrease in VPC. This is in line with the finding of the fixed effects that the utilisation of healthcare is determined by demographic and need variables more than socioeconomic variables and health insurance.

Table 6.3 Individual-level mixed-effect models for healthcare utilisation							
Model	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*	*Model 7*
				Fixed effect: coefficient (S.D.)			
Year	Reference = 2000						
2004	0.97(0.07)***	0.79(0.07)***	0.61(0.09)***	0.62(0.08)***	0.61(0.08)***	0.62(0.09)***	0.63(0.08)***
2006	0.91(0.07)***	0.65(0.07)***	0.75(0.08)***	0.76(0.07)***	0.76(0.08)***	0.74(0.08)***	0.75(0.08)***
2009	1.07(0.06)***	0.68(0.06)***	0.69(0.07)***	0.72(0.07)***	0.70(0.07)***	0.64(0.09)***	0.66(0.08)***
2011	1.03(0.07)***	0.55(0.07)***	0.68(0.08)***	0.72(0.08)***	0.70(0.08)***	0.64(0.09)***	0.65(0.09)***
Age		0.04(0.00)***	0.02(0.00)***	0.02(0.00)***	0.02(0.00)***	0.01(0.00)***	0.01(0.00)***
Gender		-0.27(0.03)***	-0.21(0.04)***	-0.20(0.04)***	-0.15(0.04)**	-0.15(0.04)***	-0.15(0.04)***
Chronic diseases			0.44(0.05)***	0.46(0.05)***	0.48(0.05)***	0.47(0.05)***	0.47(0.05)***
Health status			4.25(0.06)***	4.24(0.06)***	4.24(0.06)***	4.24(0.06)***	4.24(0.06)***
Household Income				-0.07(0.02)***	-0.03(0.02)	-0.04(0.02)*	-0.04(0.02)*
Household Size				0.05(0.01)**	0.03(0.01)*	0.03(0.01)*	0.03(0.01)*
Education	Reference = no or primary school						
Middle or tech					-0.14(0.05)*	-0.14(0.05)**	-0.14(0.05)**
University					-0.23(0.11)*	-0.25(0.12)*	-0.26(0.12)*
Working					-0.17(0.05)**	-0.18(0.05)***	-0.18(0.05)***
Hukou					0.29(0.05)***	0.25(0.06)***	0.25(0.06)***
SHI	Reference = no SHI						
FMS						0.26(0.09)**	0.25(0.09)**
Urban SHI						0.04(0.08)	0.03(0.08)
NCMS						0.17(0.07)*	0.16(0.07)*
PHI							0.10(0.12)
				Random effect: variance (S.D.)			
Individual-level	1.52(0.07)***	0.90(0.05)***	0.65(0.08)***	0.63(0.08)***	0.59(0.08)***	0.59(0.08)***	0.59(0.08)***

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,745.

Significance values: ˡp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.

6.2 Adding the community level

This section continues by adding the community level and related aggregate variables to the individual-level mixed-effect model (Table 6.3: Model 7), after a brief descriptive analysis about these aggregate variables (for more Information about the community and the choice of aggregate variables see Section 3.3 and 3.5.4).

6.2.1 Descriptive analysis

Summarising the utilisation-related community indices in the crosstab of geographies and community types (Table 6.4), it can be seen that the three utilisation-related community indices tend to be the highest in the urban east and the lowest in the rural inland, except transportation, where urban inland communities performed slightly better than their east counterparts. The urban-rural disparities appear to be greater in magnitude than the east-inland disparities. The poorest rural inland one, which always lags behind the other three, deserves particular attention in research.

Table 6.4 Summary of aggregate variables and their relationship

	East		*Inland*		*Total*
	Urban	*Rural*	*Urban*	*Rural*	
Health infrastructure	7.16(1.64)	5.47(2.28)	6.63(2.06)	4.76(2.53)	5.62(2.46)
Transportation	6.32(2.03)	5.67(2.42)	6.65(1.89)	4.93(2.42)	5.65(2.38)
Economy	9.14(1.79)	5.83(3.13)	8.79(1.99)	4.44(2.84)	6.28(3.30)

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471.[29]
Two-way ANOVA test shows that differences of these indices are all significant across the four subpopulations (for all p<0.001).

[29] A few communities have missing values for community development indexes. Because the number is very small and imputing aggregate data with individual data is not appropriate, the missing aggregate data are not imputed.

Focusing on health insurance, the dependent variable and two health insurance variables are simultaneously summarised for each subpopulation (Table 6.5). As the prevalence of SHI and PHI tends to be greater in the urban and east areas than in the rural and inland areas, the spatial differences in the utilisation of healthcare are not as visible as those in health insurance prevalence, although there are significant spatial differences in all the three. The utilisation in urban areas appears to be slightly greater than in rural areas, consistent with the distribution of SHI and PHI.

Table 6.5 Summary of aggregate variables and their relationships

	East		*Inland*		*Total*
	Urban	*Rural*	*Urban*	*Rural*	
Utilisation	0.13(0.00)	0.12(0.00)	0.13(0.00)	0.12(0.00)	0.13(0.00)
SHI	0.69(0.01)	0.64(0.00)	0.56(0.00)	0.48(0.00)	0.57(0.00)
PHI	0.10(0.00)	0.07(0.00)	0.08(0.00)	0.02(0.00)	0.05(0.00)

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 81,755.

F tests show that the utilisation of formal healthcare, prevalence of PHI and SHI as a whole are all significantly different across the four subpopulations (for all p<0.001).

6.2.2 Fitting the three-level model

Adding the community level to the established individual-level model with no new variable introduced, household income, the household size and university education lose significance (Table 6.6: Model 8). Apart from these, all the effects of the other variables remain almost unchanged. This result suggests that these individual socioeconomic characteristics appear to in part influence healthcare utilisation through their association with where the individual resides.

Subsequently, adding the geography and community type variables (Table 6.6: Model 9), both the newly-added variables are significant. Interestingly, unlike the result of the descriptive analysis, after adjusting all other factors in the model, east and urban areas, typical the more affluent, were associated with a lower average utilisation of healthcare than their inland and rural counterparts, respectively. Few coefficients of the existing variables change, except hukou, because hukou, as a residence registration institution, is closely associated with actual residence. Echoing the findings in the individual-level model, this suggests that affluence at both levels was not associated with higher generic utilisation of formal healthcare, which to large extent was determined by personal needs.

Further, adding the three community indices has little impact on the existing coefficients either (Table 6.6: Model 10). Only the index of community health infrastructure is significant, but negative, which means a community with better health infrastructure is contrarily associated with a lower average utilisation of healthcare. This is possibly because of the correlation between health infrastructure and a higher price of local health services in the community. In addition, this may again be partly attributed to the index's higher values in east and urban areas (see Table 6.4).

In terms of random effects, after both individual-level and community-level variables have been included in Model 10 (Table 6.6), the individual-level variation (variance = 0.48) is far greater than the community-level variation (variance = 0.11). The VPCs, based on the variances, signify that 3% of the residual variation in the utilisation comes from the community, while 12% of that comes from individual characteristics. This suggests that, overall, the unobserved variation in the utilisation of healthcare is determined more by personal factors than by environmental factors.

Adding the community level and all these aggregate variables into the model slightly increases the magnitude of the coefficients of SHI schemes and PHI but has no impact on significance (FMS: OR = 1.37, 95% CI 1.13 – 1.65; urban SHI: OR = 1.11, 95% CI 0.95 – 1.30; NCMS: OR = 1.18, 95% CI 1.02 – 1.35; PHI: OR = 1.14, 95% CI 0.89 – 1.46). In sum, according to the complete three-level model (Model 10), only the government FMS and the rural NCMS were significantly associated with the utilisation of healthcare compared to no SHI; For the FMS enrolees and the NCMS enrolees, the odds of using formal healthcare were 1.37 and 1.18 times as large as the odds for SHI non-enrolees using formal healthcare. PHI and the urban SHI enrolees were not significantly associated the utilisation compared to those without PHI and those without SHI, respectively.

Table 6.6 Three-level models on healthcare utilisation

Model	*Model 8*	*Model 9*	*Model 10*
Fixed effect: coefficient (S.D.)			
Year	Reference = 2000		
2004	0.64(0.08)***	0.63(0.08)***	0.62(0.09)***
2006	0.75(0.08)***	0.74(0.08)***	0.72(0.08)***
2009	0.64(0.09)***	0.62(0.09)***	0.63(0.09)***
2011	0.63(0.09)***	0.61(0.09)***	0.60(0.09)***
Age	0.01(0.00)***	0.02(0.00)***	0.02(0.00)***
Gender	-0.16(0.04)***	-0.17(0.04)***	-0.17(0.04)***
Chronic diseases	0.49(0.05)***	0.50(0.05)***	0.50(0.05)***
Health status	4.22(0.06)***	4.22(0.06)***	4.22(0.06)***
Household income	-0.02(0.02)	-0.02(0.02)	-0.01(0.02)
Household Size	0.01(0.02)	0.01(0.02)	0.01(0.02)
Education	Reference = no or primary school		
Middle or tech	-0.12(0.05)*	-0.10(0.05)ᵻ	-0.10(0.05)ᵻ
University	-0.12(0.12)	-0.10(0.012)	-0.10(0.12)
Working	-0.20(0.05)***	-0.21(0.05)***	-0.21(0.05)***
Hukou	0.19(0.06)**	0.08(0.07)	0.07(0.07)
SHI	Reference = no SHI		
FMS	0.29(0.10)**	0.32(0.10)**	0.31(0.10)**
Urban SHI	0.08(0.08)	0.11(0.08)	0.10(0.08)
NCMS	0.16(0.07)*	0.16(0.07)*	0.16(0.07)*
PHI	0.11(0.12)	0.13(0.12)	0.13(0.12)
Aggregate variables			
East		-0.27(0.06)***	-0.25(0.06)***
Urban		-0.27(0.09)**	-0.23(0.09)*
Health infrastructure			-0.03(0.01)*

Transportation			-0.01(0.01)
Economic activity			0.00(0.01)
Random effect: variance (S.D.)			
Community-level	0.12(0.02)***	0.11(0.02)***	0.10(0.02)***
Individual-level	0.48(0.08)***	0.49(0.08)***	0.49(0.08)***
Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471. Significance values: ^{t}p≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.			

6.3 Disaggregation

In this section the study population is disaggregated into four subpopulations – the urban east, the rural east, the urban inland and the rural inland, respectively. Based on each of these the final three-level model (Table 6.6: Model 10) is fitted again. In addition, for the models on subpopulations, not only are random-intercept models fitted, but models with a random slope of PHI are tried, to explore how PHI's effect varies among communities.

After disaggregation (Table 6.7: Model 10a-10d), a notable difference in time effect emerges across these subpopulations. The positive effects of the years after 2000 are all significant in the inland but generally weaker in the east. This possibly suggests that the health reforms were more inclined to promote utilisation in the inland than in the east after the year 2000. This is in line with the official statistics, which show quicker increases in hospital admissions and outpatient utilisation in western and central China (the inland) compared to in the east from 2003 to 2011 (Meng et al., 2012).

The significance of the effects of needs-related variables such as age, chronic diseases and health status, in general holds in all subpopulations. This suggests that needs are a very essential, invariant drive for healthcare. Socioeconomic variables, such as household income, the household size, education level and *hukou* remain insignificant. What is interesting is that the positive coefficient of household income and the negative coefficient of household size in the rural inland are exactly reversed in their signs, compared to those in other regions. This implies that in the poorest rural inland, individuals' utilisation appeared to be more dependent on economic affluence than in other regions. Besides, working status's negative effect is only significant in two rural regions. As this negative effect should be in part attributed to employment's close correlation with younger and healthier status, this may also imply that rural areas' relatively weak social security systems prevent working people, likely to be an essential income source for households, from stopping to see doctors.

Focusing on health insurance, the effect of SHI compared to no SHI varies heavily between regions and schemes. For urban areas, only the coefficient of government's FMS reaches or approaches significance (in the urban east, FMS: OR = 1.41, 95% CI 0.94 – 2.12; in the urban inland, FMS: OR = 1.40, 95% CI 1.04 – 1.89). For rural areas, all SHI schemes' coefficients are significant in the east (FMS: OR = 1.70, 95% CI 1.10 – 2.64; urban SHI: OR = 1.58, 95% CI 1.10 – 2.27; NCMS: OR = 1.43, 95% CI 1.11 – 1.85), but only the coefficient of the NCMS is significant in the inland (OR = 1.26, 95% CI 1.02 – 1.55).

This suggests that the FMS has wider effectiveness, possibly associated with its more comprehensive benefits, compared to other SHI schemes (Liang and Langenbrunner, 2013). The NCMS, the rural SHI with population coverage that in effect has greatly extended to urban areas due to rural-to-urban migration, was only correlated with the utilisation in rural areas, thanks possibly to its compensation being largely restricted to rural clinics (Yip and Hsiao, 2009b). In addition, the urban SHI was not significantly correlated with the utilisation in urban areas. A possible explanation is that unlike the NCMS enrolees receiving primary care in local clinics, Chinese urbanites tend to seek all kinds of healthcare in hospitals, many of which are too busy to provide convenient services, compromising the effect of the urban SHI on utilisation (Yip and Hsiao, 2014).

The effect of PHI is not significant for all subpopulations after disaggregation, compared to no PHI (urban east: OR = 1.04, 95% CI 0.65 – 1.66; rural east: OR = 1.12, 95% CI 0.78 – 1.63; urban inland: OR = 1.20, 95% CI 0.85 – 1.68; rural inland: OR = 1.13, 95% CI 0.63 – 2.02). One explicit reason for this is that many PHI policies focus on some critical diseases and complementing SHI (Liu et al., 2011b, EY, 2016b), so that their effects on promoting utilisation in the general population is very limited. Possibly, when the individual's need level for healthcare increases and thereby likelihood of receiving financial compensation from PHI increases, the effect of PHI on healthcare utilisation would change. This will be explored later in this chapter.

At the aggregate level, the effects of the three community indices are all weak for these subpopulations. Only the negative effect of health infrastructure on utilisation reaches marginal significance in the rural inland. Maybe in poor areas, since better health infrastructure means pricier medicine and medical services, the locals are less able to afford healthcare.

In terms of random effects, the community-level variances of utilisation (the random intercept) are significant for the two inland subpopulations, and much smaller and insignificant for the two east subpopulations, while the individual-level variances of intercept among the four subpopulations are all significant and stronger than the community-level variances. This suggests that for unobserved variation in healthcare utilisation, while personal factors still dominated in all regions, community-level heterogeneity was greater in the inland than in the east.

Trying to explore whether the effect of PHI was different across communities (the random slope), the coefficient of PHI is allowed to vary between communities in Model 11a – 11b (Table 6.7). As a result, the coefficients of the random slope are insignificant in all four subpopulations. Moreover, the effects of other independent variables almost hold the same after adding the random slope. This suggests that the simpler random-intercept model (Model 10a-10b) seems preferable to the random slope model (Model 11a-11b), for the sake of efficiency.[30]

Notwithstanding this, the values of the random effect of PHI coefficient still give information. By comparing their substances, the effect of PHI is seen to vary heavier among communities in the rural areas, especially in the rural inland (the random slope variance = 0.13 for the rural east and 0.50 for the rural inland), compared to the two urban areas (the random slope variance = 0.05 for the urban east and 0.06 for the urban inland). This suggests that the effects of PHI on healthcare utilisation are more homogenous across communities in urban areas than in rural areas, especially the poorest rural inland. This may be related to the relative concordance in the urban healthcare systems, on which PHI's performance must depend, compared with the uneven quality and quantity levels within the rural healthcare systems.

[30] In principle, the conclusion should be made with the outcome of a likelihood ratio test, which, however, cannot apply to multiply-imputed data in the statistical package. Consequently, only the result of the Wald test is referred to.

Table 6.7 The disaggregated models on healthcare utilisation with a random PHI effect or not								
	Urban east		*Rural east*		*Urban inland*		*Rural inland*	
Model	*Model 10a*	*Model 11a*	*Model 10b*	*Model 11b*	*Model 10c*	*Model 11c*	*Model 10d*	*Model 11d*
Fixed effect: coefficient (S.D.)								
Year	Reference = 2000							
2004	0.24(0.25)	0.24(0.25)	0.45(0.18)*	0.45(0.18)*	0.63(0.15)***	0.63(0.15)***	0.77(0.11)***	0.77(0.11)***
2006	0.36(0.25)	0.36(0.25)	0.26(0.20)	0.27(0.21)	0.88(0.14)***	0.88(0.14)***	0.85(0.11)***	0.85(0.12)***
2009	0.40(0.28)	0.40(0.28)	0.29(0.18)	0.29(0.18)	0.75(0.15)***	0.75(0.15)***	0.62(0.14)***	0.63(0.14)***
2011	0.87(0.30)**	0.87(0.30)**	0.32(0.19)†	0.32(0.19)	0.66(0.17)***	0.66(0.17)***	0.46(0.14)**	0.46(0.14)**
Age	0.02(0.01)**	0.02(0.01)**	0.01(0.00)*	0.01(0.00)*	0.02(0.00)***	0.02(0.00)***	0.01(0.00)***	0.01(0.00)***
Gender	-0.19(0.12)	-0.19(0.12)	-0.29(0.09)**	-0.29(0.09)**	-0.12(0.08)	-0.12(0.08)	-0.15(0.06)*	-0.15(0.06)*
Chronic diseases	0.48(0.12)***	0.48(0.12)***	0.49(0.11)***	0.50(0.11)***	0.48(0.10)***	0.48(0.10)***	0.57(0.09)***	0.57(0.09)***
Health status	4.16(0.16)***	4.16(0.16)***	4.35(0.12)***	4.35(0.12)***	4.00(0.10)***	4.00(0.10)***	4.38(0.09)***	4.39(0.09)***
Household income	-0.03(0.06)	-0.03(0.06)	-0.05(0.05)	-0.05(0.05)	-0.05(0.04)	-0.05(0.04)	0.03(0.03)	0.03(0.03)
Household size	0.07(0.05)	0.07(0.05)	0.02(0.03)	0.02(0.03)	0.03(0.03)	0.03(0.03)	-0.02(0.02)	-0.02(0.02)
Education	Reference = no or primary school							
Middle or tech	0.01(0.16)	0.01(0.16)	0.06(0.10)	0.06(0.10)	-0.20(0.11)†	-0.20(0.11)†	-0.15(0.08)†	-0.15(0.08)†
University	-0.05(0.25)	-0.05(0.25)	-0.28(0.27)	-0.28(0.28)	-0.17(0.16)	-0.17(0.16)	-0.38(0.32)	-0.36(0.32)
Working	-0.10(0.15)	-0.10(0.15)	-0.36(0.11)**	-0.36(0.11)**	-0.14(0.09)	-0.14(0.09)	-0.24(0.07)**	-0.24(0.07)**
Hukou	0.29(0.25)	0.29(0.25)	0.05(0.15)	0.05(0.15)	0.05(0.15)	0.05(0.15)	-0.12(0.12)	-0.11(0.12)
SHI	Reference = no SHI							
FMS	0.34(0.21)†	0.34(0.21)†	0.53(0.22)*	0.53(0.22)*	0.34(0.15)*	0.34(0.15)*	0.08(0.27)	0.07(0.27)
Urban SHI	0.06(0.17)	0.06(0.17)	0.46(0.18)*	0.46(0.18)*	0.07(0.11)	0.07(0.11)	-0.01(0.18)	-0.01(0.18)

NCMS	0.35(0.25)	0.35(0.25)	0.36(0.13)**	0.36(0.13)**	0.18(0.19)	0.18(0.19)	0.23(0.11)*	0.22(0.11)*
PHI	0.03(0.24)	0.02(0.25)	0.12(0.19)	0.10(0.20)	0.18(0.17)	0.16(0.18)	0.12(0.29)	0.06(0.34)
Aggregate variables								
Health infrastructure	-0.02(0.04)	-0.02(0.04)	-0.04(0.03)	-0.04(0.03)	0.02(0.03)	0.02(0.03)	-0.03(0.01) ǂ	-0.03(0.01) ǂ
Transportation	-0.01(0.04)	-0.01(0.04)	-0.00(0.02)	-0.00(0.02)	-0.02(0.03)	-0.02(0.03)	-0.00(0.02)	-0.00(0.02)
Economic activity	-0.03(0.03)	-0.03(0.03)	0.03(0.02)	0.03(0.02)	0.02(0.02)	0.02(0.02)	0.00(0.01)	0.00(0.01)
Random effect: variance (S.D.)								
Community-level								
Cons	0.07(0.05)	0.07(0.05)	0.05(0.03)	0.05(0.03)	0.11(0.05)*	0.11(0.05)*	0.11(0.03)***	0.11(0.03)***
PHI		0.05(0.16)		0.13(0.27)		0.06(0.12)		0.50(0.60)
Individual-level								
Cons	0.52(0.21)*	0.52(0.21)*	0.55(0.17)**	0.55(0.17)**	0.49(0.15)**	0.49(0.15)**	0.45(0.10)***	0.45(0.10)***

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471 (Urban east: n=9265; Rural east: n=17210; Urban inland: n=19400; Rural inland: n=34870).
Significance values: ǂp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.

6.4 Temporal variation of insurance effect

Because the method of handling longitudinal data involves pooling them within individuals, as in the last chapter, this section checks whether the health insurance variables vary in their effects on healthcare utilisation over time, in case valuable information is masked by average effects. For simplicity and abased on background knowledge, two ends of this study period, i.e. 2000 and 2011, are examined compared to other years.

As a result, between the year 2000 and the post-2000 years (2004 – 2011), no significant interaction between the time transition and any health insurance scheme has been found in the models based on the whole population and the four subpopulations, while the Chow tests show a significant change in coefficients of PHI and SHI schemes between the two time periods for the whole population, the urban inland and rural inland (Table 6.8).[31] Between the years 2000 – 2009 and the year 2011, only the interaction between the time transition and the urban SHI is significant based on the whole population (OR = 1.72, 95% CI 1.05 – 2.81), while there is no significant interaction in the models based on subpopulations. The Chow tests show a significant change in coefficients of PHI and SHI schemes between the two time periods for the whole population, the urban east and urban inland (Table 6.9).

Taken together, the outcomes of the Chow test suggest splitting the data by time would be suitable for estimating the effects of PHI and SHI on healthcare utilisation due to the temporal change. However, first, slitting data by time is essentially not very appropriate for longitudinal data, in which data collected in different years are correlated to each other if they belong to the same individual or group. Second, the Chow test only examines an overall coefficient pattern of the set of health insurance

[31] The Chow test tests the main effect of the time transition and their interactions with health insurance schemes being equal to 0.

schemes. Regarding particular interactions, few of them are significant, and there is no such widespread, uniform change as those in the impacts of SHI on PHI enrolment between 2000 and the years after 2000 (Section 5.4.2). On balance, this study does not split the longitudinal data in this chapter.

Table 6.8 Difference of insurance effect on utilisation between 2000 and later years

	Total	*Urban east*	*Rural east*	*Urban inland*	*Rural inland*
Model	Model 12	Model 12a	Model 12b	Model 12c	Model 12d
Post-2000‡	0.70(0.09)***	0.31(0.31)	0.37(0.20)†	0.75(0.16)***	0.83(0.11)***
SHI	Reference = no SHI				
FMS	0.28(0.11)*	0.38(0.24)	0.59(0.27)*	0.31(0.17)†	-0.04(0.28)
Urban SHI	0.08(0.07)	0.22(0.17)	0.42(0.18)*	0.07(0.11)	-0.18(0.17)
NCMS	0.12(0.07)†	0.43(0.28)	0.36(0.12)**	0.15(0.18)	0.04(0.08)
Post-2000×FMS	-0.06(0.23)	-0.14(0.50)	0.50(0.59)	-0.05(0.33)	-0.20(0.58)
Post-2000×Urban SHI	0.11(0.25)	0.03(0.50)	0.77(0.62)	0.10(0.35)	-0.04(0.68)
Post-2000×NCMS	-0.42(0.26)	-0.11(0.71)	0.13(0.35)	-0.53(0.75)	-0.97(0.70)
PHI	0.05(0.17)	0.17(0.33)	0.05(0.24)	0.16(0.25)	-0.18(0.38)
Post-2000×PHI	-0.14(0.25)	0.37(0.55)	-0.36(0.46)	0.01(0.38)	-0.55(0.68)

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471 (Urban east: n = 9265; Rural east: n = 17210; Urban inland: n = 19400; Rural inland: n = 34870).
Significance values: †p≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.
Adjusted for demographic, socioeconomic and aggregate variables like those in Model 10.
‡ Post-2000 refers to the 2004, 2006, 2009 and 2011 waves of data of the CHNS.
The chow tests show a significant change in coefficients of PHI and SHI schemes between the two periods for the whole population (p<0.001), the urban inland (p<0.001), and rural inland (p<0.001).

Table 6.9 Difference of insurance effects on utilisation between 2000-2009 and 2011

	Total	*Urban east*	*Rural east*	*Urban inland*	*Rural inland*
Model	Model 13	Model 13a	Model 13b	Model 13c	Model 13d
Post-2009‡	0.42(0.21)†	0.76(0.54)	-0.33(0.59)	0.46(0.29)	0.50(0.36)
SHI	Reference = no SHI				
FMS	0.33(0.10)**	0.39(0.21)†	0.57(0.23)*	0.41(0.15)**	0.16(0.28)
Urban SHI	-0.05(0.09)	0.04(0.19)	0.25(0.18)	-0.01(0.13)	-0.09(0.21)
NCMS	0.22(0.07)**	0.45(0.27)†	0.38(0.14)**	0.32(0.22)	0.23(0.11)*
Post-2009×FMS	-0.13(0.29)	-0.13(0.72)	0.11(0.88)	-0.35(0.41)	-0.57(0.75)

Post-2009×Urban SHI	0.54(0.25)*	0.13(0.53)	1.08(0.65)	0.39(0.32)	0.15(0.42)
Post-2009×NCMS	0.04(0.23)	-0.42(0.70)	0.48(0.60)	-0.19(0.46)	-0.04(0.37)
PHI	0.06(0.13)	-0.08(0.26)	0.01(0.22)	0.09(0.19)	0.18(0.30)
Post-2009×PHI	0.37(0.26)	0.77(0.59)	0.49(0.41)	0.60(0.45)	-0.32(0.61)

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471 (Urban east: n=9265; Rural east: n=17210; Urban inland: n=19400; Rural inland: n=34870).
Significance values: ǂp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.
Adjusted for demographic, socioeconomic and aggregate variables like those in Model 10.
‡ Post-2009 refers to the 2011 data of the CHNS.
The chow tests show a significant change in coefficients of PHI and SHI schemes between the two periods for the whole population (p<0.001), the urban east (p<0.05) and the urban inland (p<0.001).

6.5 PHI's varying effect with need

A goal of national health insurance is to protect access for those in need of healthcare (Scheil-Adlung, 2013: 14). As the theoretical frame suggests (Section 1.3.2), health insurance coverage could generate sub-optimal additional utilisation due to price reduction, that is, the moral hazard (Pauly, 1968). However, if the additional utilisation is predominately consumed by those who are ill (hence in need of healthcare), it should result from a social-welfare-gain transfer of income from the healthy to the ill more than the inefficient moral hazard (Nyman, 2006). From a health policy point of view, it is also good to see more people is consuming needed healthcare.

The variable called health status in this study, indicating whether the individual considers him/herself ill or injured in the past four weeks of the survey, plausibly reflects whether the individual has developed a physiological or psychological condition in greater need of medical attention in this period, compared to those who consider themselves not ill or injured. In theory, the additional utilisation attributable to those who are ill or injured are in general more efficient than that attributable to those who are not. For terminological simplicity, I call the former the high-need group and the latter the low-need group. It would be interesting to explore the interactions between the need level and enrolment into health insurance schemes on healthcare utilisation.

The interactions between PHI and the need level are all positive and significant for the whole and marginally significant for the urban east, the rural east and the urban inland, except the rural inland (Table 6.10). This suggests that PHI was more associated with the utilisation for the high-need group than it was for the low-need group. Considering magnitude, this shows a pattern – in the high-need group, those with PHI were significantly more associated with the utilisation of healthcare than those without PHI (based on the whole population, OR = 1.45, 95% CI 1.06 – 1.99), but there was no such difference between PHI status in the low-need group (based on the whole population, OR = 0.83, 95% CI 0.56 – 1.22).

By contrast, most interactions between the need level and SHI schemes are negative and significant for many (Table 6.10). Combined with the positive main effects of SHI schemes, this suggests that in the low-need group SHI enrolees were more associated with using healthcare than those without SHI (based on the whole population, FMS: OR = 1.68, 95% CI 1.27 – 2.22; urban SHI: OR = 1.65, 95% CI 1.39 – 1.97; NCMS: OR = 1.29, 95% CI 1.09 – 1.52), while in the high-need group the difference in the utilisation between SHI enrolees and non-enrolees significantly reduced (based on the whole population, FMS: OR = 1.14, 95% CI 0.90 – 1.45; urban SHI: OR = 0.80, 95% CI 0.66 – 0.96; NCMS: OR = 1.09, 95% CI 0.91 – 1.31).

Table 6.10 Interaction between health insurance and the personal need level

	Total	*Urban east*	*Rural east*	*Urban inland*	*Rural inland*
Model	Model 14	Model 14a	Model 14b	Model 14c	Model 14d
Need‡	4.45(0.08)***	4.43(0.30)***	4.77(0.19)***	4.11(0.15)***	4.61(0.12)***
SHI	Reference = no SHI				
FMS	0.52(0.14)***	0.65(0.34)†	0.99(0.32)**	0.30(0.21)	0.26(0.34)

Urban SHI	0.50(0.09)***	0.37(0.30)*	1.08(0.24)***	0.29(0.14)*	0.42(0.20)*
NCMS	0.25(0.08)**	0.41(0.37)	0.62(0.17)***	0.10(0.25)	0.38(0.12)**
Need×FMS	-0.39(0.18)*	-0.48(0.41)	-0.77(0.42)†	-0.07(0.28)	-0.46(0.45)
Need×Urban SHI	-0.73(0.10)***	-0.50(0.34)	-1.10(0.26)***	-0.41(0.18)*	-0.88(0.27)**
Need×NCMS	-0.17(0.10)†	-0.02(0.55)	-0.43(0.21)*	0.20(0.33)	-0.36(0.14)*
PHI	-0.19(0.20)	-0.57(0.45)	-0.27(0.31)	-0.22(0.31)	0.12(0.35)
Need×PHI	0.56(0.22)*	0.97(0.52)†	0.67(0.39)†	0.65(0.35)†	0.05(0.49)

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471 (Urban east: n=9265; Rural east: n=17210; Urban inland: n=19400; Rural inland: n=34870).
Significance values: †p≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.
Adjusted for demographic, socioeconomic and aggregate variables like those in Model 10.
‡ Need level, equal to self-reported illness or injury (1 means being ill or at high-need level; 0 means being not ill or at low-need level).

A possible explanation is that PHI, often as complementary insurance, provides more generous compensation than SHI, along with a higher threshold of making claims, however (EY, 2016b). On the contrary, SHI, focusing on basic benefits, has a relatively low threshold of compensation (Liang and Langenbrunner, 2013). According to Nyman (2006), theoretically in China PHI appeared less vulnerable to the moral hazard than SHI schemes, because PHI appeared more responsive to illness (and hence health need) than SHI. Furthermore, for the ill or injured whose needs for healthcare were unmet by SHI, PHI might be able complement SHI in promoting utilisation.

The same interactions based on the four subpopulations have similar patterns to those based on the whole population (Table 6.10), suggesting that the phenomenon is widespread across the country. On the public side, the negative interaction between an SHI scheme and the need level is generally weaker in urban areas, especially in the urban east (all negative interactions between SHI scheme and the need level are not significant), compared to the rural areas, especially the rural inland, possibly because SHI coverage is more generous in more affluent urban areas than in poorer rural areas. On the private side, magnitude of the interaction between PHI and the need level is the greatest in the urban east (OR = 2.64, 95% CI 0.95 – 7.34), followed by the rural east and the urban inland (OR = 1.96, 95% CI 0.90 – 4.26; OR = 1.92, 95% CI 0.96 – 3.85, respectively), with marginal significance for the three, but it is very little in the poorest rural inland (OR = 1.05, 95% CI 0.40 – 2.77). It suggests that PHI appeared more responsive to the need in the more affluent areas than the poorer areas in China.

Finally, it is worth noting that the findings themselves cannot lead to causal inferences that health insurance coverage impacted healthcare utilisation, due to the limitation of the study design. Instead, they are just associations. Further interpretation about these associations between health insurance and utilisation are presented in the discussion chapter.

6.6 The dual insurance effect on access

Because people can have SHI and PHI at the same time, how the two work together and influence each other deserves examination. In addition, it is worth exploring a more complex three-way interaction between PHI, SHI and the need level. In practice, because membership of SHI schemes is correlated to urban/rural residence, for subpopulations, an extremely small number of observations may occur for some combinations of an SHI scheme, PHI and the high need, consequently leading to failure of model convergence. To address this problem, this section replaces the categorical SHI variable with a simplified binary variable indicating membership of any SHI scheme. The compromise should be worthwhile, given the similar patterns of SHI schemes' effects in many cases.

The result is presented in the following table (Table 6.11). For the models with only the two-way interaction between PHI and SHI, the interaction is insignificant for the whole population and the four subpopulations (Table 6.11: Model 15, 15a – 15d). The three-way interaction between PHI, SHI and the need level is positive and significant for the whole population (OR = 3.38, 95% CI 1.45 – 7.82) (Table 6.11: Model 16). This suggests that, overall, for the high-need group, the correlations of SHI and PHI with the utilisation were mutually enhancing, but they were not for the low-need group. Importantly, it is worth noting that after adding the three-way interaction, the two-way interaction between PHI and the need level loses significance and turns negative, which means that PHI's positive correlation with the utilisation for the high-need group actually relied greatly on SHI's existence.

For the three-way-interaction models based on the subpopulations (Table 6.11: Model 16a – 16d), the three-way interactions are all positive and that in the rural east reaches marginal significance, and the two-way interactions between PHI and the need level are positive in the urban areas and negative in the rural areas, suggesting that PHI's positive correlation with the utilisation relied more on SHI in the rural areas. In terms of magnitude, for the high-need group, the combination of SHI and PHI was all more associated with the utilisation compared to no insurance coverage (based on the whole population, OR = 1.66, 95% CI 1.14 – 2.41), and the association was on average higher than that of the single coverage of either PHI (OR = 0.79, 95% CI 0.47 – 1.33) or SHI (OR = 0.93, 95% CI 0.80 – 1.08).

Likewise, in terms of magnitude, the associations with the utilisation of the combination of SHI and PHI are relatively smaller in the poorest rural inland (OR = 1.19, 95% CI 0.47 – 3.00) than that in the urban east (OR = 1.77, 95% CI 0.84 – 3.68), the rural east (OR = 2.05, 95% CI 1.06 – 4.01) and the urban inland (OR = 1.93, 95% CI 1.15 – 3.27).

Table 6.11 Interaction between SHI and PHI on healthcare utilisation

	Total		*Urban east*		*Rural east*		*Urban inland*		*Rural inland*	
Model	*Model 15*	*Model 16*	*Model 15a*	*Model 16a*	*Model 15b*	*Model 16b*	*Model 15c*	*Model 16c*	*Model 15d*	*Model 16d*
Need	4.22(0.06)***	4.47(0.08)***	4.16(0.15)***	4.48(0.27)***	4.34(0.12)***	4.81(0.20)***	3.99(0.11)***	4.13(0.15)***	4.38(0.09)***	4.62(0.12)***
SHI	0.14(0.06)*	0.37(0.07)***	0.16(0.15)	0.48(0.27)ǂ	0.40(0.13)**	0.78(0.18)***	0.13(0.09)	0.28(0.13)*	0.20(0.10)ǂ	0.38(0.11)**
PHI	-0.06(0.24)	0.14(0.34)	-0.09(0.51)	-0.20(1.02)	0.04(0.36)	0.33(0.64)	-0.06(0.36)	-0.19(0.69)	0.24(0.48)	0.56(0.48)
PHI×SHI	0.27(0.24)	-0.41(0.36)	0.22(0.59)	-0.39(1.16)	0.10(0.39)	-0.75(0.72)	0.37(0.40)	-0.07(0.72)	-0.21(0.56)	-0.72(0.65)
Need×SHI		-0.45(0.08)***		-0.51(0.32)		-0.70(0.20)**		-0.30(0.17)ǂ		-0.44(0.14)**
Need×PHI		-0.37(0.38)		0.19(1.17)		-0.52(0.76)		0.15(0.73)		-0.81(0.87)
Need×PHI×SHI		1.22(0.43)**		1.00(1.32)		1.58(0.91)ǂ		0.79(0.78)		1.20(1.10)

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471 (Urban east: n=9265; Rural east: n=17210; Urban inland: n=19400; Rural inland: n=34870).

Significance values: ǂp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.

Adjusted for demographic, socioeconomic and aggregate variables like those in Model 10.

6.7 The contextual effect of insurance programmes

A persistent concern about PHI is that it may benefit its members at the expense of others by allocating health resources depending on membership rather than needs (Colombo, 2007). On the contrary, to contribute to UHC, an insurance programme needs to do well enough to upgrade the efficiency of the whole system (Kutzin, 2013). From this point of view, a primary question arises: how the health insurance scheme impacts, as a contextual effect, individuals' healthcare utilisation in surrounding areas on average.

To investigate the contextual effect following the existing method (Schempf and Kaufman, 2012), this section introduces a new community-level variable, PHI prevalence level, which indicates the prevalence of PHI in the community by computing the proportion of PHI enrolment within the community in each survey wave. Using the same method, it also introduces the community's SHI prevalence level (combining all SHI schemes together) for reference, and the community's need level (the proportion of the community residents who were ill or injured) as a control. The three variables, and the interactions between the PHI prevalence level and the need level, and between the SHI prevalence level and the need level, are introduced into the model successively (Table 6.12).

As a result, based on the whole population, all coefficients of the PHI prevalence level are insignificant, while the SHI prevalence level (OR = 0.67, 95% CI 0.51 – 0.87) and the interaction between the SHI prevalence level and the need level (OR = 0.07, 95% CI 0.02 – 0.35) are significantly negative (Table 6.12: Model 17 and Model 18). This suggests that the prevalence of PHI in the community had little association with the average utilisation in the community, whereas the SHI prevalence level was negatively associated with the average utilisation in the community; a one unit increase in the SHI prevalence level led to a 0.67 time reduction in the community average odds of using formal healthcare. As the need level increased, the negative contextual effect of SHI was enhanced.

As aforementioned, a possible explanation for this result is that, while SHI expanded and increased its members' access to healthcare, the provision resources did not increase at the same rate, resulting in a rising strain on local healthcare delivery that actually prevented other residents from accessing healthcare. A vivid example is public hospitals' congestion and rising charges (Yip and Hsiao, 2014), more or less intensified by the expansion of SHI, which may reduce locals' willingness to go to hospital on average.

Looking at the disaggregated subpopulations, for the two east subpopulations, the model coefficient profiles are similar, as the effects of the three newly-introduced variables are all negative, but hardly reach significance (Table 6.12: Model 17a and 17b). The interactions between the PHI prevalence level and the need level are substantially positive, approaching significance in the rural east, but the two main effects are still negative (Table 6.12: Model 18a and 18b). This suggests that in the east the PHI prevalence level was increasingly associated with higher average utilisation in the community as the community need level increased; in east China, PHI tends to contribute to equity of utilisation, since it was increasingly associated with higher average utilisation in response to increasing average needs in the whole community. By contrast, the interaction between the SHI prevalence level and the need level is weak.

The patterns for the two inland subpopulations are different from each other and from the east. Both coefficients of the PHI prevalence level in the inland are not significant. By contrast, the effect of the SHI prevalence level is significantly negative in the urban inland (OR = 0.52, 95% CI 0.29 – 0.93), but small in the rural inland (Table 6.12: Model 17c and 17d). This indicates that in the urban inland the higher prevalence of

SHI was associated with lower average utilisation in the community, similar to the east. The interactions between the PHI prevalence level and the need level, and between the SHI prevalence level and the need level, are both negative, especially in the rural inland, where both interactions are significant (for PHI: OR = $7.29*10^{-11}$, 95% CI $2.12*10^{-19}$ – 0.03; for SHI: OR = 0.14, 95% CI 0.02 – 0.94) (Table 6.12: Model 18c and 18d). This indicates that in the inland as the need level increased, the prevalence of both SHI and PHI was increasingly associated with lower average utilisation in the community, seemingly making healthcare utilisation more inequitable.

In sum, the analysis offers an insight into healthcare utilisation inequity associated by the contextual effects of health insurance in China. A clear pattern is that both SHI's and PHI's contextual effects seem more pro-equity in the east than in the inland. This possibly relates to local health resources, richer in the more affluent east. In areas where heath resources are insufficient, typically poorer inland villages, the increased level of insurance coverage, which encourages the enrolees to use healthcare, intensifies resource strain, and the tighter market of healthcare could raise the local level of medical bills (Babiarz et al., 2010, Fu et al., 2014, Jing et al., 2013), preventing those uncovered by health insurance from accessing healthcare.

Table 6.12 The contextual effect of health insurance coverage on average healthcare utilisation										
	Total		*Urban east*		*Rural east*		*Urban inland*		*Rural inland*	
Model	*Model 17*	*Model 18*	*Model 17a*	*Model 18a*	*Model 17b*	*Model 18b*	*Model 17c*	*Model 18c*	*Model 17d*	*Model 18d*
PHI level	0.02(0.31)	0.25(0.53)	-0.11(0.72)	-1.41(1.24)	-0.17(0.44)	-1.29(0.80)	0.84(0.68)	1.22(1.10)	-0.06(1.16)	2.59(1.40)ǂ
SHI level	-0.41(0.13)**	-0.05(0.18)	-0.25(0.48)	-0.19(0.64)	-0.06(0.28)	0.25(0.35)	-0.66(0.30)*	-0.12(0.42)	0.01(0.23)	0.22(0.29)
Need level	-0.21(0.30)	1.64(0.57)**	-0.67(0.85)	-1.22(2.51)	-0.95(0.55)ǂ	-0.28(1.36)	-0.20(0.58)	1.98(1.30)	1.15(0.45)*	2.71(0.76)**
PHI level×need level		-1.70(2.32)		11.50(8.79)		5.60(3.25)ǂ		-3.18(5.32)		-23.34(9.92)*
SHI level×need level		-2.62(0.78)**		-0.28(2.95)		-1.50(1.56)		-3.38(2.00)ǂ		-2.00(0.98)*

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471 (Urban east: n=9265; Rural east: n=17210; Urban inland: n=19400; Rural inland: n=34870).

Significance values: ǂp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.

Adjusted for demographic, socioeconomic and aggregate variables like those in Model 10.

Conclusion

Based on the general population, enrolment into PHI was not correlated with the utilisation of formal healthcare. By contrast, enrolment into some SHI schemes, including the FMS and the NCMS, was significantly associated with a utilisation increase, compared to those without SHI. Health insurance's effects on utilisation were basically steady over time. The increase of the personal need level (falling ill or injured) significantly enhanced the positive association between PHI and the utilisation to reach significance, but significantly reduced the positive correlations between all SHI schemes and the utilisation so as to lose significance. Further analysis finds that PHI's association with utilisation for the high-need group only happened in the presence of SHI. PHI seems to be complementing SHI in promoting utilisation for enrolees in need of healthcare.

In terms of spatial differences, for the high-need group the effects of PHI as well as the effects of dual insurance of PHI and SHI on utilisation tended to be weaker in the poorer rural inland than in other areas. Furthermore, PHI's effect on healthcare utilisation varied among communities remarkably more in rural areas, especially the rural inland, than in urban areas. Unequal effects on utilisation also exist in SHI: the government's FMS was widely associated with healthcare utilisation, except in the rural inland; the NCMS was only associated with healthcare utilisation in rural areas, although it also covered considerable urban residents; the urban SHI had little effect at all. From the low-need group to the high-need group, SHI's correlation with the utilisation reduced further in rural areas than in urban areas, implying poorer SHI benefits coverage in rural areas. Therefore, PHI has not complemented the spatial inequality of utilisation that SHI made and might have rather increased it.

In terms of the contextual effects of health insurance on the community's average utilisation, in the east, the PHI prevalence level was increasingly associated with higher average utilisation in the community as the community need level increased; contrarily, in the inland as the need level increased, the prevalence of both SHI and PHI was increasingly associated with lower average utilisation in the community. This suggests a pattern whereby both SHI and PHI are more pro-equity in the east than in the inland, due possibly to an unequal richness of local health resources, in favour of the more affluent east.

Chapter Seven: Financial Protection of PHI

The final results chapter presents the investigation into the financial protection of private health insurance (PHI), in comparison with social health insurance (SHI) in China. Data for the analysis are still extracted from the five waves of the China Health and Nutrition Survey (CHNS) dataset from 2000 to 2011. Financial protection of a health insurance scheme, as formulated in Chapter 3, is indicated by the scheme's impact on out-of-pocket (OOP) payments for healthcare, a widely-used measure of financial risk caused by healthcare utilisation in the literature.

In theory, using costly healthcare does not necessarily raise financial risk, which can be prevented by insurance compensation. Rather, it is OOP expenditure, the payments net of insurance reimbursement, that decides financial risk (Van Doorslaer et al., 2007), and also influences health inequity by preventing the poor from using needed healthcare (Krutilova and Yaya, 2012). For a health system, the share of OOP payments needs to stay below 15-20% of total health expenditure, to effectively control the incidence of financial risk, according to the World Health Organisation (WHO, 2010a). In China, this proportion has lingered at 30% or more, despite the rapid scale up of SHI (National Health and Family Planning Commission, 2013). As a consequence, the incidence of overall Chinese households experiencing catastrophic health expenditure persists at above 12% (Meng et al., 2012), worse than most developing countries (Li et al., 2012d).

Though it has been often suggested as a promising solution to SHI's inadequacy (Gu, 2009a, Xiang, 2014, Blomqvist, 2009), PHI's financial protection is controversial internationally (Bos and Waters, 2008, Holst and Gericke, 2012, Salti et al., 2010). The literature review of this thesis shows little evidence for PHI's financial protection in China as well. In addition, some international studies have questioned PHI's role in financial equity (Su et al., 2006, Xu et al., 2006, Onwujekwe et al., 2014, Sekhri and Savedoff, 2005), while there is a lack of evidence about PHI's impact at the system level in China, thanks to the scarce and fragmented studies in the literature.

What is more, technically, modelling health expenditure is not straightforward due to the zero-piled and highly-skewed data distribution (O'Donnell et al., 2008: 131-145). At the beginning of this chapter, I try to justify my choice of models by presenting the pros and cons of the candidates and analysing the degree to which the method satisfies my research purpose. Following the justification of the selected models are descriptive statistics. In the remaining sections, the outcomes of the Heckman models and the ZINB models, with independent variables added step by step, are presented and interpreted, followed by disaggregation in the same way as in the last two chapters. After these, temporal variation, interactions between SHI and PHI, as well as the contextual effects of health insurance schemes, are examined.

7.1 Justification for modelling health expenditure

A linear estimator is not an appropriate method for modelling health expenditure data (O'Donnell et al., 2008: 131-145). The reason for this, first of all, is the fact that, for standard household surveys, during a short recall period (latest four weeks in the CHNS dataset) health expenditures are often unobserved or recorded as zero simply because of no utilisation (for details see Table 7.2). Treating values of these cases to be either missing or zero, ordinary least square (OLS) estimates on the whole sample are very likely to violate the basic assumption of error normality, and hence result in estimation bias (Wooldridge, 2015: 47, Wooldridge, 2002: 560-566).

To overcome this problem, hurdle models such as the Two-Part model, the Tobit model and the sample-selection model are popular for modelling health expenditure data (O'Donnell et al., 2008: 131-145). By contrast, the Tobit model and the Two-Part models, which separate zeros from positive values of the dependent variable, are not very appropriate for this case, because in the CHNS dataset some people paid zero for healthcare due to the coverage of health insurance. The meaning of zero payment to healthcare users is different from that to non-users.

Other than the former two, the sample selection, or Heckman model, selects cases depending on the value of another variable rather than the value of the dependent variable itself (Heckman, 1979). Regarding this research, the Heckman model can select cases based on utilisation at the first step, not mixing zero OOP payments from healthcare users and non-users, and at the second step it can model health expenditure solely on the users. Additionally, unlike the Two-Part model, the Heckman model assumes that the two steps, i.e. the decision to utilise and the decision to spend in this study, are correlated (Heckman, 1979). This makes sense for the process of healthcare utilisation (O'Donnell et al., 2008: 131-145), especially in the case of China, where OOP payments may be considerable enough to impact the decisions to use healthcare (Liu et al., 2011a, You and Kobayashi, 2011).

The second equation of the original Heckman model uses an OLS estimator. Although the first step has eliminated a number of zeros, the remaining healthcare users' zeros due to health insurance coverage and the heavily right-skewed distribution of positive values may still cause the OLS estimator to struggle. An arguable coping strategy is adding a small positive number to replace zero and then log-transforming the expenditure data. However, the validity of this method and even log-transformation itself have been long questioned as it significantly reduces data variability, making estimation non-comparable to the original one and difficult to interpret (Linders and De Groot, 2006, Sileshi, 2006, Changyong et al., 2014).

An alternative method is recoding the continuous expenditure variable to a categorical variable (Saei et al., 1996) and previously used in modelling Chinese health expenditure data (Fang et al., 2012). Accordingly, the estimator of the second equation of the Heckman model is altered from OLS to probit. There are reasons for this choice. First, a well-defined threshold of health expenditure should be able to signify financial risk by an incidence, just like the method used to define catastrophic health expenditure (Xu et al., 2007). Second, this method does not rigidly separate zeros from positive values, which seems plausible from the economic prospective. For instance, the difference in the financial impact between zero and a small payment like ¥10 (¥1≈ £0.11 or $0.14) is negligible, and far less significant than the difference between two positive payments such as ¥100 and ¥1000. Third, technically, the Heckman-probit estimator has been well established and is easily realised in statistical packages.[32]

Notwithstanding these advantages, the Heckman-probit model oversimplifies expenditure information by transforming continuous data to binary data. An alternative is a zero-inflated count model, with either an assumption of Poisson distribution (ZIP) or negative binomial distribution (ZINB), which is able to unbiasedly model expenditure without substantial artificial transformation (Min and Agresti, 2002). With a simple requirement of rounding health expenditure values to integers[33] to treat expenditure as count data, count models are effectively immune from heteroskedasticity and normality assumptions of errors, which would undermine linear

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[32] There is another potential choice called the Heckman-Poisson model (Miranda and Rabe-Hesketh, 2005), which has not yet been officially built in the statistical package that I can access.

[33] In this case, round the decimal of health spending up to the smallest integer not less than the decimal (took the ceiling) rather than the nearest integer, to avoid increasing zeros.

models (Tran et al., 2012, Gould, 2011). Particularly, zero-inflated models assume that for the dependent variable a certain proportion of values are necessarily zero, while the rest still follow a distribution with a positive probability of zero (Lambert, 1992, Hall, 2000). This assumption well matches the fact of the research data, in which most people necessarily spent zero due to no utilisation, while some healthcare users possibly spent zero due to insurance coverage. Between ZIP and ZINB, the latter is preferable to the former for this research, because negative binomial distribution is more suitable for over-dispersed data like health expenditure (Min and Agresti, 2002).

It is worth noting that while using any of the models mentioned above, it is technically difficult to maintain the multilevel structure used before. As far as I know, no previous studies have developed either Heckman models or ZINB models with multilevel structures. A basic obstacle would be, mathematically, how to treat the correlation between two equations' errors within the model. In practice, it is unfeasible to realise the model by using built-in commands in statistical packages. Additionally, in terms of standard survey datasets, compared to the whole, the sample size of OOP payers for healthcare often reduces significantly, possibly causing trouble for multilevel modelling. Actually, the literature review shows that many previous studies on health expenditure based on Chinese survey data simply used single-level models (Chen et al., 2009, You and Kobayashi, 2011, Liu et al., 2011a, Fang et al., 2012). Taking all the factors discussed previously together, for the sake of model validity, it may be more beneficial to use the Heckman model or the ZINB model than to use the ordinary modelling method with a multilevel structure.

Giving up the multilevel structure does not mean ignoring the longitudinal data structure. The modelling, based on maximal likelihood estimation with variance component estimation (VCE) in which observations cluster in the individual is applied (cluster-robust standard errors), is able to take the within-individual correlation of longitudinal data into account. In terms of the nested-in relationship between individuals and communities, although there is a lack of the community level in the model, community-level indices indicating the health-related development of the community are included in the model as variables. They more or less bring in information about the community variation, hopefully mitigating the negative impact of the absence of the community level.

In this study, both the Heckman-probit models and the ZINB models are used for cross-reference. Before presenting the model outcomes, there is a section that generally describes the origin of the model dependent variables, OOP health payments, and its relationships with independent variables, to provide an overview of the correlations between the expenditure and its determinants. Then, the research proceeds to the Heckman models, to examine the effects of health insurance on the incidence of exceeding the 50th percentile of OOP health payments data (medium risk) and the incidence of exceeding the 90th percentile of OOP health payments data (high risk). The presentation of the Heckman model results is followed by the section about the ZINB models, which directly estimate the effects of health insurance on the amount of OOP health payments. Like the last chapter, the remaining part of this chapter also sets out to disaggregate the population and then examine the temporal variation of the health insurance effect, dual insurance of PHI and SHI, and the contextual effects of health insurance, successively.

7.2 Descriptive statistics

Table 7.1 presents the summary of the dependent variables for the Heckman model and the ZINB model, respectively.[34] For the Heckman model, the variable of healthcare utilisation, the dependent variable in the last chapter, serves as the dependent variable for the first equation of the model. The two binary variables indicate whether the amount of OOP health payments exceeded the median level and the 90th percentile level are the dependent variables for the second equation to indicate the medium level and high level of financial risk, respectively. For the ZINB model, the binary variable indicates whether the OOP payment was zero for the first equation, and the amount of OOP payments as a count for the second equation. More details are presented later, along with the corresponding analyses.

Table 7.1 Overview of dependent variables for the Heckman model and ZINB model

Variable	*Description*	*Mean(S.D.)*	*Min/Max*
Heckman Model			
Healthcare utilisation	Whether used formal healthcare in past four weeks	0.13(0.50)	0/1
*Payment > 50%**	Whether the OOP payments for healthcare were more than those 50% of healthcare users paid	0.50(0.56)	0/1
*Payment > 90%**	Whether the OOP payments for healthcare are more than those 90% of healthcare users paid	0.10(0.31)	0/1
ZINB Model			
Payment = 0	Whether the OOP payment for healthcare is zero	0.16(0.53)	0/1
*Payment as a count*ƚ	OOP payments for healthcare inflated to 2011 consumer price index, rounded as an integer	155.53(2982.43)	0/90543

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 81,755;
*n = 10,099 (Only including healthcare users).
ƚ Unit: Chinese Yuan (¥).

[34] Specification of model independent variables for OOP health payments is very similar to those for healthcare utilisation, for the reasons that have been elaborated previously (Section 4.3.3). Thus, the same variables are not repeatedly summarised here.

Before going into the transformed dependent variables, the following part of this section briefly explores the original OOP health payments (inflated to 2011 consumer price index, or CPI), as a prelude to the analyses. At first glance, these OOP payments are characterised by a number of zeros (Table 7.2: left hand): based on the whole population, the value at the 75th percentile is still zero in all five survey years. This makes sense, because most people did not use healthcare at all in the recall period (last four weeks) as they simply had no need to do so. Nonetheless, the remaining ten percentiles see the value of health payment quickly rises from the 90th percentile to the 99th percentile.

Taking into account utilisation[35], the average OOP expenditure of healthcare non-users is low, while, by contrast, the average OOP expenditure of healthcare users is substantially higher and fluctuates over time (Table 7.2: right hand). Notably, it reached a relatively high level in 2011, even if the SHI system meanwhile achieved the greatest population coverage (Meng et al., 2012). The summary of expenditure percentiles for healthcare users shows an evidently right-skewed distribution. Some users reported zero OOP payment (more than 10% except in 2004). The median expenditure, and even the 75th percentile expenditure, are less than the mean, but they increase quickly at the 90th percentile onwards. This suggests that most users paid little or a moderate amount, while a few bore extremely high payments and thus were vulnerable to financial catastrophe. In sum, this result appears to underpin my justification of the model choice.

[35] The dependent variable in the last chapter, i.e. whether using formal healthcare (outpatient or inpatient care) in the four weeks before the survey.

Table 7.2 Summarising health payments by years among the whole population and healthcare users

Year	*Whole population*						*Healthcare*							
	Mean	*Percentiles*					*Non-users*	*Users*	*Percentiles (Users)*					
		50%	*75%*	*90%*	*95%*	*99%*	*Mean*		*10%*	*25%*	*50%*	*75%*	*90%*	*95%*
2000	96.95(31.95)	0	0	0	44.25	1370.35	5.81(3.61)	1417.56(470.55)	0	21.06	130.84	617.63	2348.58	4838.98
2004	185.71(21.24)	0	0	95.23	394.29	3746.09	29.78(4.55)	1163.21(153.43)	2.96	29.03	132.76	529.43	2093.44	4648.89
2006	129.57(14.26)	0	0	66.27	294.12	2474.20	18.30(3.80)	859.48(107.05)	0	20.51	107.38	420.42	1465.39	3158.76
2009	164.15(22.46)	0	0	100.93	391.84	3270.96	22.27(3.89)	979.73(149.64)	0	22.86	126.72	502.63	1809.32	3830.34
2011	200.91(26.13)	0	0	88.15	438.69	3998.23	29.44(5.64)	1219.96(178.66)	0	13.59	115.30	572.45	2296.09	4773.51
Total	155.46(10.43)	0	0	58.37	307.73	2968.12	20.84(1.77)	1094.81(83.57)	0	25.21	119.10	466.85	1804.78	4087.27

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 81,755.

Unit: Chinese Yuan (¥).

F tests shows that difference in the mean of OOP payments are significant across years for the whole population and healthcare non-users ($p<0.05$ and $p<0.001$, respectively), but not significant for healthcare users ($p=0.32$).

Cross-tabulating the whole population and the population of healthcare users by SHI and PHI memberships and summarising OOP payments (Table 7.3), we find that the PHI enrolees paid on average more than those without PHI, regardless of whether they were part of the whole population or users. In addition, the standard deviations for PHI enrolees were substantially greater than those for the non-enrolees, suggesting that the effect of PHI on OOP payments appeared to vary considerably. On the SHI side, only the urban scheme has a similar pattern to PHI, compared to those without SHI, while the FMS and the NCMS appear to be correlated to lower average OOP payments than those without SHI among the users. Those with both PHI and a SHI scheme paid less than those with only PHI, but they paid more than those with only the corresponding SHI scheme, especially for the users. In sum, those with PHI appeared to bear higher OOP payments than those without it, while enrolment into SHI had the reverse relationship.

Briefly exploring correlations between OOP health payments and remaining individual-level independent variables (Table 7.4), OOP payments have positive relationships with age, the diagnostic history of chronic diseases and health status, and negative relationships with other variables. This profile is very similar to the correlations between healthcare utilisation and these individual variables (Table 6.2). Except health status, which strongly determines utilisation, the correlations with most variables are all weak, for the reason that this computation is based on the whole population, among whom most individuals spent zero on healthcare. The descriptive analyses based on the users are presented in the following section, along with the models.

Table 7.3 Summarising health payments by insured status						
	Whole population			*Healthcare users*		
	No PHI	*PHI*	*Total*	*No PHI*	*PHI*	*Total*
No SHI	132.41(12.35)	233.31(176.01)	135.19(12.97)	1150.87(120.18)	1942.44(1728.26)	1172.39(124.11)
FMS	200.02(66.03)	128.80(131.28)	183.28(54.48)	1104.38(422.66)	1207.14(1331.10)	1121.21(381.52)
Urban SHI	214.61(31.04)	234.33(318.99)	215.84(37.60)	1273.20(205.37)	1648.37(2262.34)	1295.41(258.89)
NCMS	137.69(13.85)	184.37(105.87)	139.51(13.09)	855.65(94.90)	1370.17(906.28)	872.48(89.01)
Total	153.52(9.76)	192.03(97.48)	155.46(10.43)	1073.87(77.55)	1544.77(861.84)	1094.81(83.57)

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 81,755.

FMS = government employees' scheme; NCMS = rural SHI schemes.

Unit: Chinese Yuan (¥).

F tests show that difference in the mean of OOP payments between PHI status, and between SHI status are all not significant for the whole population and for the healthcare users.

Table 7.4 Correlations of OOP health expenses and demographic and socioeconomic variables

	OOP	*Age*	*Gender*	*Chronic diseases*	*Health status*	*Household income*	*Household size*	*Education*	*Working*	*Hukou*
OOP	1.00									
Age	0.05	1.00								
Gender	-0.00	-0.00	1.00							
Chronic diseases	0.07	0.35	0.01	1.00						
Health status	0.15	0.23	-0.04	0.25	1.00					
Household income	-0.00	-0.07	0.01	0.01	-0.03	1.00				
Household size	-0.01	-0.18	-0.00	-0.10	-0.04	0.23	1.00			
Education	-0.02	-0.40	0.15	-0.10	-0.10	0.19	-0.02	1.00		
Working	-0.05	-0.46	0.16	-0.23	-0.16	0.14	0.09	0.17	1.00	
Hukou	-0.02	-0.11	-0.01	-0.13	-0.05	-0.12	0.19	-0.30	0.24	1.00

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 81,755.

Unit of expenses: Chinese Yuan (¥).

OOP = OOP payment for healthcare.

Computation referred to a user-written programme in Stata to handle the multiply-imputed data (Eddings and Marchenko, 2010).

7.3 Modelling OOP health payments

As discussed above, this section sets out to employ the Heckman-probit model and the ZINB model, successively, with their specified dependent variables transformed from the original OOP payment for healthcare. The independent variables are added step by step as previously. Estimation with cluster-robust standard errors is used to deal with the longitudinal data structure, instead of multilevel modelling.

7.3.1 The Heckman model: two levels of financial risk

The Heckman models estimate the incidence of individuals spending over the 50^{th} percentile and the 90^{th} percentile of health expenditure among all formal healthcare users, respectively. This study defines spending over the median as medium financial risk, and spending over the 90^{th} percentile as high financial risk.[36] Table 7.5 summarises the two dependent variables depending on SHI and PHI coverage status. For the incidence of medium risk, enrolees of SHI schemes, especially the government's FMS and the rural NCMS, appeared to have a lower chance of the incidence than those without SHI on average, while enrolees of PHI have a just slightly lower chance of the incidence than those without PHI. For the incidence of high risk, the difference between SHI status almost diminished, while enrolees of PHI even appeared to have a higher chance than those without PHI.

Table 7.5 Summary of the dependent variables over SHI and PHI status

	OOP Payment>50%			*OOP Payment>90%*		
	No PHI	*PHI*	*Total*	*No PHI*	*PHI*	*Total*
No SHI	0.54(0.50)	0.52(0.50)	0.54(0.50)	0.11(0.31)	0.11(0.32)	0.11(0.31)
FMS	0.44(0.50)	0.45(0.50)	0.44(0.50)	0.09(0.29)	0.12(0.33)	0.10(0.29)
Urban SHI	0.52(0.50)	0.49(0.50)	0.52(0.50)	0.12(0.33)	0.12(0.32)	0.12(0.33)

[36] The median and the 90th percentile are derived from data across all years rather than one for each year. Because all payments have been inflated to the 2011 CPI, data from different years are comparable.

NCMS	0.46(0.50)	0.46(0.50)	0.46(0.50)	0.08(0.28)	0.16(0.37)	0.09(0.28)
Total	0.50(0.50)	0.48(0.50)	0.50(0.50)	0.10(0.30)	0.13(0.34)	0.10(0.30)

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 81,755.
FMS = government employees' scheme; NCMS = rural SHI schemes.
Computation is based on only healthcare users and estimates are derived from means of all imputation. Significance tests for difference are not feasible for this case.

After the brief descriptive analysis, independent variables are added step by step into the model. As aforementioned, the Heckman model has two equations. The model first estimates the probability of healthcare utilisation based on the whole population (the selection equation), and then the probability of exceeding the threshold based on the selected sample (the outcome equation). Although the incidences of medium risk and high risk are estimated separately in two models, their selection equations are in effect identical.

Additionally, the Heckman model mathematically requires the selection equation to include at least one variable not included in the outcome model. These variables are expected to be relevant to the selection process but irrelevant to the second outcome equation (Heckman, 1979). In this case, health status is selected to play this role, for the reason that theoretically, health status decides whether or not a patient sees a doctor, but may have relatively little influence on OOP payments for healthcare, which, instead, is more likely to be determined by the result of diagnosis, the doctor, the patient's affluence and insurance coverage.[37]

Since utilisation was investigated in the last chapter, the following analysis focuses only on the second equation. Model 1 (Table 7.6) initially includes year dummies to capture unobserved variations related to time, referring to 2000. These effects are in general little, except the negative effect of the year 2006 on high financial risk,

[37] Based on the study sample, the correlation between health status and utilisation is 0.72, and the correlation between health status and OOP payments of the users is merely 0.01, supporting this model specification.

possibly related to the expansion of the rural NCMS since 2004 (Yip et al., 2012). From Model 2 to Model 4, background variables are added, from demographic ones to socioeconomic ones, step by step. The effects of the history of chronic diseases, the household size and working status are significant on both levels of financial risk. Adding new background variables generally has only a small impact on the coefficients of existing ones, except the effect of age, which rises to significance (marginal significance for high financial risk) in Model 4, due possibly to its correlation with non-working status.

Model 5 (Table 7.6) includes the SHI variable. For medium financial risk, all SHI schemes have significant negative effects compared to no SHI (FMS: OR = 0.69, 95% CI 0.60 – 0.79; urban SHI: OR = 0.84, 95% CI 0.74 – 0.95; NCMS: OR = 0.79, 95% CI 0.72 – 0.87); In terms of magnitude, the government's FMS is the most effective and the urban SHI schemes are the least; this means that for the enrolees of FMS, urban SHI and NCMS, the odds of encountering medium financial risk were 0.69, 0.84 and 0.79 times as large as the odds for those without SHI encountering medium financial risk, respectively, when they used formal healthcare.

For high financial risk, only the rural NCMS has a significantly negative effect (OR = 0.83, 95% CI 0.72 – 0.96) and the effect of FMS is marginally significant (OR = 0.84, 95% CI 0.69 – 1.02), both with lowered magnitude, while urban SHI has little effect (OR = 0.94, 95% CI 0.79 – 1.11). This suggests that SHI's financial protection against OOP payments seems overall more effective in preventing medium financial risk than high financial risk.

By contrast, in terms of PHI, it shows no significant effect on both levels of financial risk (for medium risk, OR = 1.04, 95% CI 0.88 – 1.22; for high risk, OR = 1.16, 95% CI 0.92 – 1.47), and adding it has little impact on the existing variables (Model 6). This suggests that enrolment in PHI may have little effect on reducing the financial risk related to healthcare utilisation. This result is consistent with the outcome of the descriptive analyses (Table 7.3 and 7.5).

After including all individual variables, the geography variable and the community type variable are added into the model (Table 7.6: Model 7). Only the former is significant for medium financial risk, suggesting that living in the east was positively associated with the occurrence of medium financial risk caused by using healthcare, while they are both not significant for the occurrence of high financial risk. Adding the two variables likewise has little impact on existing individual variables.

Finally, five community development indices are added (Table 7.6: Model 8), which measure the levels of health infrastructure, transportation infrastructure, economy activity, social services and population density in the community, respectively. They help to control unobserved community variation to compensate the impact of the lack of a community level in the model. For those reaching significance, the index of transportation and the index of social services (marginally) have positive correlations with medium financial risk, while the population density has a negative correlation with it. For high financial risk, only the population density has a marginally significant negative effect. In addition, taking into account the community-level measurements, the model coefficient profile almost holds the same, which suggests that community factors may not seriously interfere with the individual ones and thus the influence from the lack of the multilevel structure should be acceptable.

Table 7.6 The Heckman-probit models on financial risk

Model	*Model 1a*	*Model 1b*	*Model 1c*	*Model 2a*	*Model 2b*	*Model 2c*	*Model 3a*	*Model 3b*	*Model 3c*
Equation	*Selection*	*>50%*	*>90%*	*Selection*	*>50%*	*>90%*	*Selection*	*>50%*	*>90%*
				Fixed effect: coefficient (S.D.)					
Year	Reference = 2000								
2004	0.38(0.04)***	0.06(0.06)	-0.02(0.09)	0.36(0.04)***	0.06(0.06)	-0.02(0.09)	0.37(0.04)***	0.06(0.06)	-0.03(0.09)
2006	0.47(0.03)***	-0.03(0.06)	-0.18(0.09)*	0.42(0.03)***	-0.04(0.06)	-0.19(0.09)*	0.43(0.03)***	-0.03(0.06)	-0.19(0.09)*
2009	0.47(0.03)***	0.02(0.06)	-0.09(0.08)	0.39(0.03)***	0.01(0.06)	-0.11(0.08)	0.41(0.03)***	0.02(0.06)	-0.12(0.09)
2011	0.49(0.03)***	-0.03(0.06)	0.02(0.08)	0.38(0.03)***	-0.05(0.06)	-0.01(0.08)	0.40(0.03)***	-0.04(0.07)	-0.00(0.08)
Age				0.01(0.00)***	-0.00(0.00)	-0.00(0.00)	0.01(0.00)***	-0.00(0.00)	-0.00(0.00)
Gender				-0.10(0.02)***	-0.04(0.03)	0.03(0.04)	-0.10(0.02)***	-0.03(0.03)	0.03(0.04)
Chronic diseases				0.22(0.02)***	0.22(0.04)***	0.23(0.05)***	0.23(0.03)***	0.21(0.04)***	0.22(0.05)***
Household income							-0.04(0.01)***	0.01(0.02)	0.02(0.02)
Household size							0.03(0.01)***	-0.04(0.01)**	-0.03(0.01)*
Health status	2.31(0.02)***			2.19(0.02)***			2.19(0.02)***		

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471.

Significance values: †p≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.

Table 7.6 Continued

Model	*Model 4a*	*Model 4b*	*Model 4c*	*Model 5a*	*Model 5b*	*Model 5c*	*Model 6a*	*Model 6b*	*Model 6c*
Equation	*Selection*	*>50%*	*>90%*	*Selection*	*>50%*	*>90%*	*Selection*	*>50%*	*>90%*
				Fixed effect: coefficient (S.D.)					

Year	Reference = 2000								
2004	0.36(0.04)***	0.05(0.07)	-0.04(0.09)	0.37(0.04)***	0.04(0.07)	-0.04(0.09)	0.37(0.04)***	0.04(0.07)	-0.02(0.09)
2006	0.43(0.03)***	-0.04(0.06)	-0.20(0.09)*	0.42(0.03)***	-0.02(0.06)	-0.18(0.09)*	0.43(0.03)***	-0.01(0.06)	-0.16(0.09)ǂ
2009	0.40(0.03)***	0.02(0.07)	0.12(0.09)	0.37(0.04)***	0.11(0.08)	-0.05(0.10)	0.38(0.04)***	0.12(0.08)	-0.03(0.10)
2011	0.40(0.04)***	-0.04(0.07)	-0.01(0.08)	0.37(0.04)***	0.06(0.08)	0.05(0.09)	0.37(0.04)***	0.06(0.08)	0.08(0.09)
Age	0.01(0.00)***	-0.00(0.00)*	-0.00(0.00)ǂ	0.01(0.00)***	-0.00(0.00)*	-0.00(0.00)	0.01(0.00)***	-0.00(0.00)*	-0.00(0.00)ǂ
Gender	-0.07(0.02)***	-0.02(0.03)	0.05(0.05)	-0.07(0.02)***	-0.01(0.04)	0.05(0.05)	-0.07(0.02)***	-0.01(0.03)	0.06(0.05)
Chronic diseases	0.24(0.03)***	0.18(0.04)***	0.19(0.05)***	0.24(0.03)***	0.19(0.04)***	0.20(0.05)***	0.24(0.03)***	0.19(0.04)***	0.20(0.05)***
Household income	-0.02(0.01)ǂ	0.01(0.02)	0.02(0.02)	-0.02(0.01)*	0.03(0.02)ǂ	0.03(0.02)	-0.02(0.01)*	0.03(0.02)ǂ	0.03(0.02)
Household size	0.02(0.01)*	-0.03(0.01)**	-0.03(0.01)*	0.02(0.01)*	-0.04(0.01)**	-0.03(0.01)*	0.02(0.01)*	-0.04(0.01)**	-0.03(0.01)*
Education	Reference = no or primary school								
Middle or tech	-0.06(0.03)*	0.04(0.04)	0.06(0.05)	-0.07(0.03)*	0.06(0.04)	0.06(0.06)	-0.07(0.03)**	0.06(0.04)	0.06(0.06)
University	-0.09(0.05)ǂ	-0.07(0.08)	0.08(0.11)	-0.10(0.06)ǂ	-0.02(0.08)	0.09(0.11)	-0.10(0.06)ǂ	-0.02(0.08)	0.09(0.11)
Working	-0.08(0.02)***	-0.20(0.05)***	-0.26(0.06)***	-0.09(0.02)***	-0.19(0.05)***	-0.25(0.06)***	-0.09(0.02)***	-0.19(0.05)***	-0.25(0.06)***
Hukou	0.13(0.02)***	-0.08(0.04)ǂ	-0.03(0.05)	0.12(0.03)***	-0.08(0.05)	0.01(0.06)	0.12(0.03)***	-0.08(0.05)	0.02(0.06)
SHI	Reference = no SHI								
FMS				0.13(0.04)**	-0.37(0.07)***	-0.18(0.10)ǂ	0.12(0.05)**	-0.38(0.07)***	-0.20(0.10)ǂ
Urban SHI				0.02(0.4)	-0.18(0.06)**	-0.07(0.09)	0.02(0.04)	-0.18(0.06)**	-0.07(0.09)
NCMS				0.08(0.03)*	-0.23(0.05)***	-0.18(0.07)*	0.08(0.03)*	-0.23(0.05)***	-0.19(0.07)**
PHI							0.05(0.06)	0.03(0.08)	0.15(0.12)
Health status	2.20(0.02)***			2.20(0.02)***			2.20(0.02)***		
Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471.									
Significance values: ǂp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.									

Table 7.6 Continued						
Model	*Model 7a*	*Model 7b*	*Model 7c*	*Model 8a*	*Model 8b*	*Model 8c*
Equation	*Selection*	*>50%*	*>90%*	*Selection*	*>50%*	*>90%*
Fixed effect: coefficient (S.D.)						
Year	Reference = 2000					
2004	0.37(0.04)***	0.04(0.07)	-0.02(0.09)	0.39 (0.04)***	0.02(0.07)	-0.05(0.09)
2006	0.42(0.03)***	-0.00(0.06)	-0.16(0.09)ǂ	0.44(0.04)***	-0.03(0.07)	-0.20(0.09)*
2009	0.36(0.04)***	0.13(0.08)ǂ	-0.02(0.10)	0.40(0.04)***	0.10 (0.08)	-0.07(0.10)
2011	0.36(0.04)***	0.08(0.08)	0.08(0.09)	0.38(0.04)***	0.06(0.08)	0.05(0.10)
Age	0.01(0.00)***	-0.00(0.00)ǂ	-0.00(0.00)ǂ	0.01(0.00)***	-0.00(0.00)ǂ	-0.00(0.00)
Gender	-0.08(0.02)***	-0.00(0.03)	0.06(0.05)	-0.08(0.02)***	-0.00(0.03)	0.06(0.05)
Chronic diseases	0.25(0.03)***	0.18(0.04)***	0.19(0.05)***	0.25(0.03)***	0.18(0.04)***	0.19(0.05)***
Household income	-0.02(0.01)ǂ	0.02(0.02)	0.03(0.02)	-0.01(0.01)	0.02(0.02)	0.02(0.02)
Household size	0.01(0.01)*	-0.04(0.01)**	-0.03(0.01)*	0.01(0.01)ǂ	-0.03(0.01)**	-0.03(0.01)ǂ
Education	Reference = no or primary school					
Middle or tech	-0.06(0.03)*	0.06(0.04)	0.06(0.06)	-0.05(0.03)*	0.05(0.04)	0.06(0.06)
University	-0.10(0.06)ǂ	-0.02(0.08)	0.09(0.11)	-0.08(0.06)	-0.02(0.08)	0.09(0.11)
Working	-0.09(0.02)***	-0.19(0.05)***	-0.25(0.06)***	-0.10(0.02)***	-0.18(0.05)***	-0.24(0.06)***
Hukou	0.07(0.03)*	-0.07(0.06)	0.02(0.07)	0.04(0.03)	-0.03(0.06)	0.05(0.07)
SHI	Reference = no SHI					
FMS	0.14(0.05)**	-0.38(0.07)***	-0.20(0.10)ǂ	0.14(0.05)**	-0.39(0.07)***	-0.20(0.10)ǂ
Urban SHI	0.05(0.04)	-0.20(0.07)**	-0.08(0.08)	0.06(0.04)	-0.20 (0.06)**	-0.08(0.08)
NCMS	0.09(0.03)**	-0.26(0.05)***	-0.20(0.07)**	0.09(0.03)**	-0.26(0.05)***	-0.21(0.07)**
PHI	0.06(0.06)	0.03(0.08)	0.15(0.12)	0.07(0.06)	0.02(0.08)	0.15(0.12)

Health status	2.20(0.02)***			2.20(0.02)***		
Aggregate variables						
East	-0.12(0.02)***	0.10(0.04)*	0.05(0.06)	-0.11(0.02)***	0.11(0.04)**	0.07(0.06)
Urban	-0.07(0.03)*	-0.01(0.05)	-0.02(0.06)	-0.03(0.03)	-0.05(0.06)	-0.04(0.07)
Health infrastructure				-0.01(0.00)*	0.01(0.01)	0.00(0.01)
Transportation				-0.01(0.00)	0.02(0.01)*	0.02(0.01)
Economic activity				0.00(0.00)	0.01(0.01)	0.01(0.01)
Social services				-0.02(0.00)***	0.01(0.01) ǂ	0.01(0.01)
Population				-0.01(0.01)	-0.03(0.02)*	-0.04(0.02) ǂ
Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471. Significance values: ǂp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.						

7.3.2 The ZINB model: the amount of payments

In this section, the ZINB model is applied to estimate effects on OOP payments rounded to be integers. The ZINB model also consists of two equations. The first logit equation estimates the occurrence of zero values, and the second negative binomial equation estimates OOP payments as count data. To be consistent and comparable, basically the same regressors were included as in the Heckman model[38], despite no such mathematical requirement being specified for the ZINB model.

The ZINB model and the Heckman model look alike in terms of structure and the modelling process. However, the coefficient interpretations are different. As well as their dissimilar second equations as aforementioned, the first equations of the two models also provide distinct information: the Heckman model estimates the utilisation of healthcare, while the ZINB model estimates the occurrence of zero OOP payment for healthcare. Since zero expenditure in a large part correlates with no utilisation, the signs of the variable coefficients in the two first equations should be opposite to each other if their estimations are consistent. But we need to bear in mind that using healthcare does not necessarily lead to an OOP payment in the presence of health insurance.

Moving on to the results of the ZINB models, from Model 9 to Model 12 (Table 7.7), as expected, the coefficient signs of the background variables in the logit equation are generally opposite to those in the selection equation of the Heckman model (Table 7.6). This means that factors that increase the utilisation of healthcare in the Heckman model indeed reduce the occurrence of zero OOP payment in the ZINB model. The estimations of the two models therefore seem basically consistent. In terms of the

[38] This means that the variable of health status is included in the logit equation, but not included in the count equation of the ZINB model. The same logic as that used in the Heckman model could be applied here, that health status determines whether or not an individual sees the doctor, which is strongly associated with whether or not they spend zero, while its influence on specific expenditure is weak.

second equation, the results are generally similar to those of the Heckman model as well. The history of chronic diseases and working status are positively and negatively correlated to the amount of OOP health payments, respectively. Moreover, like the Heckman model on the high risk, the year 2006 is associated with a lower OOP payment in the ZINB model.

With respect to health insurance, compared to no SHI, the government's FMS and the rural NCMS are significantly positively correlated to the occurrence of zero OOP payment (FMS: OR = 1.44, 95% CI 1.10 – 1.89; urban SHI: OR = 1.08, 95% CI 0.93 – 1.25; NCMS: OR = 1.18, 95% CI 1.01 – 1.39), while the effects of all SHI schemes on the amount of OOP payments, although negative, are not significant; the effects of urban SHI schemes are weaker than the other two in both cases (Table 7.7: Model 13); it means that for the enrolees of the FMS and NCMS, the odds of paying zero OOP for healthcare were 1.44 and 1.18 times as large as the odds for those without SHI paying zero OOP for healthcare. Together with previous findings of SHI schemes' positive correlations with healthcare utilisation, this suggests that SHI offered some forms of healthcare free of charge (likely to be lower-end basic services and medicine), in comparison with those without SHI; once OOP payments happened (more advanced care was used), SHI was not able to effectively compensate the costs to reduce the amount of OOP payments.

In contrast, PHI is negatively associated with the occurrence of zero OOP payment with marginal significance (OR = 0.76, 95% CI 0.54 – 1.05), and has an insignificant correlation with the amount of OOP payments (Table 7.7: Model 14). This suggests that maybe PHI promoted the utilisation of healthcare not fully covered by health insurance (hence likely to be advanced medical services or medicine), and thus increase the probability of positive OOP payments, in comparison with no PHI. This contrast between SHI and PHI is in line with the argument made in the last chapter that SHI focuses on basic benefits while PHI often operates as complementary or supplementary insurance. From a different perspective, PHI seemingly managed to increase utilisation without significantly increasing OOP payments caused by utilisation.

Additionally, since the second equation of the Heckman model is conditional on the utilisation of healthcare, while the ZINB model is not, it would be interesting to add the utilisation variable as an independent variable into the ZINB model. As a result, it is significant in both equations, as expected correlated to the lower probability of zero OOP payment and the higher amount of OOP payments. After controlling utilisation, the positive effects of SHI schemes on the occurrence of zero OOP payment are strengthened (FMS: OR = 2.19, 95% CI 1.57 – 3.06; urban SHI: OR = 1.24, 95% CI 1.01 – 1.52; NCMS: OR = 1.36, 95% CI 1.10 – 1.67), while little change happens to their effects on the amount of OOP payments. However, PHI loses the marginal significance of its negative effect on the occurrence of zero OOP payment (OR = 0.82, 95% CI 0.57 – 1.17) (Table 7.7: Model 15). This outcome supports the inference that PHI may increase the occurrence of positive OOP payments due to boosting (advanced) utilisation, while SHI may increase (basic) utilisation and fully compensate some of them so as to increase the occurrence of zero OOP payment.

After the geographic variable and the community type variable are added into the model (Table 7.7: Model 16), both are not significant for the two equations, having little impact on the existing variables. Finally, the community development indices are included (Table 7.7: Model 17). Health infrastructure, transportation (marginally) and population density have significantly negative correlations with the occurrence of zero OOP payment. Transportation (marginally) and social services have significantly positive correlations, and population density has a marginally significantly negative correlation, with the amount of OOP payments. The effects of the community indices on the amount of OOP payments in the ZINB model (Table 7.7: Model 17b) match well with the result of the Heckman model on medium financial risk (Table 7.6: Model 8b), suggesting concordance between the two models' outcomes again.

Table 7.7 The ZINB models on OOP payments

Model	*Model 9a*	*Model 9b*	*Model 10a*	*Model 10b*	*Model 11a*	*Model 11b*	*Model 12a*	*Model 12b*
Equation	*%Zero*	*Count*	*%Zero*	*Count*	*%Zero*	*Count*	*%Zero*	*Count*
Fixed effect: coefficient (S.D.)								
Year	Reference = 2000							
2004	-3.29(0.26)***	-0.29(0.32)	-3.27(0.27)***	-0.28(0.25)	-3.27(0.27)***	-0.28(0.26)	-3.27(0.27)***	-0.29(0.25)
2006	-3.20(0.26)***	-0.52(0.30)ǂ	-3.13(0.27)***	-0.57(0.25)*	-3.14(0.28)***	-0.57(0.25)*	-3.15(0.27)***	-0.61(0.26)*
2009	-3.19(0.26)***	-0.38(0.28)	-3.05(0.27)***	-0.46(0.25)ǂ	-3.07(0.28)***	-0.46(0.25)ǂ	-3.09(0.28)***	-0.47(0.24)ǂ
2011	-2.97(0.26)***	-0.08(0.31)	-2.77(0.27)***	-0.17(0.28)	-2.79(0.27)***	-0.16(0.27)	-2.80(0.27)***	-0.15(0.28)
Age			-0.01(0.00)***	0.01(0.00)ǂ	-0.01(0.00)***	0.01(0.00)ǂ	-0.01(0.00)**	-0.00(0.01)
Gender			0.27(0.05)***	0.08(0.12)	0.27(0.05)***	0.08(0.12)	0.24(0.06)***	0.13(0.12)
Chronic diseases			-0.77(0.06)***	0.64(0.12)***	-0.77(0.06)***	0.63(0.12)***	-0.74(0.06)***	0.59(0.12)***
Household income					0.03(0.02)	0.01(0.05)	0.04(0.03)	0.04(0.05)
Household size					0.01(0.02)	-0.02(0.03)	0.00(0.02)	-0.03(0.03)
Education	Reference = no or primary school							
Middle or tech							0.07(0.06)	-0.00(0.13)
University							-0.09(0.12)	0.07(0.33)
Working							0.15(0.07)*	-0.65(0.15)***
Hukou							0.13(0.06)*	0.03(0.10)
Health status	-19.65(8.47)*		-24.86(10.56)*		-22.10(14.05)		-23.71(9.70)*	

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471.

Significance values: ǂp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.

Table 7.7 Continued

Model	*Model 13a*	*Model 13b*	*Model 14a*	*Model 14b*	*Model 15a*	*Model 15b*	*Model 16a*	*Model 16b*	*Model 17a*	*Model 17b*
Equation	*%Zero*	*Count*	*%Zero*	*Count*	*%Zero*	*Count*	*%Zero*	*Count*	*%Zero*	*Count*
	Fixed effect: coefficient (S.D.)									
Year	Reference = 2000									
2004	-3.28(0.25)***	-0.31(0.25)	-3.30(0.27)***	-0.27(0.24)	-1.62(0.10)***	-0.08(0.23)	-1.63(0.10)***	-0.08(0.23)	-1.65(0.11)***	-0.16(0.23)
2006	-3.19(0.25)***	-0.60(0.25)*	-3.20(0.27)***	-0.57(0.24)*	-1.47(0.12)***	-0.40(0.23)ǂ	-1.48(0.12)***	-0.38(0.24)	-1.51(0.12)***	-0.49(0.24)ǂ
2009	-3.18(0.25)***	-0.44(0.27)	-3.18(0.28)***	-0.40(0.26)	-1.55(0.14)***	-0.22(0.24)	-1.57(0.14)***	-0.21(0.24)	-1.53(0.14)***	-0.29(0.25)
2011	-2.91(0.25)***	-0.13(0.29)	-2.90(0.27)***	-0.07(0.28)	-1.22(0.14)***	0.14(0.26)	-1.24(0.14)***	0.16(0.27)	-1.26(0.15)***	0.129(0.27)
Age	-0.01(0.00)***	-0.00(0.01)	-0.01(0.00)***	-0.00(0.01)	-0.00(0.00)	-0.00(0.01)	-0.00(0.00)	-0.00(0.01)	-0.00(0.00)	-0.00(0.01)
Gender	0.24(0.06)***	0.14(0.12)	0.24(0.06)***	0.14(0.12)	0.20(0.06)**	0.17(0.11)	0.19(0.06)**	0.18(0.11)	0.18(0.06)**	0.17(0.11)
Chronic diseases	-0.75(0.06)***	0.61(0.12)***	-0.75(0.06)***	0.60(0.12)***	-0.52(0.07)***	0.50(0.11)***	-0.51(0.07)***	0.50(0.11)***	-0.50(0.07)***	0.49(0.11)***
Household income	0.03(0.02)	0.05(0.06)	0.03(0.03)	0.05(0.05)	-0.01(0.04)	0.05(0.04)	-0.01(0.04)	0.04(0.05)	-0.00(0.04)	0.04(0.04)
Household size	0.01(0.02)	-0.03(0.03)	0.00(0.02)	-0.03(0.03)	0.04(0.02)ǂ	-0.04(0.03)	0.04(0.02)ǂ	-0.04(0.04)	0.04(0.02)ǂ	-0.03(0.03)
Education	Reference = no or primary school									
Middle or tech	0.06(0.06)	0.02(0.13)	0.06(0.06)	0.00(0.13)	0.01(0.07)	0.04(0.12)	0.02(0.07)	0.04(0.12)	0.05(0.07)	0.03(0.11)
University	-0.13(0.12)	0.11(0.32)	-0.11(0.12)	0.06(0.30)	-0.12(0.15)	0.18(0.26)	-0.11(0.15)	0.19(0.27)	-0.07(0.15)	0.16(0.26)
Working	0.14(0.07)ǂ	-0.63(0.14)***	0.14(0.07)ǂ	-0.65(0.14)***	0.05(0.08)	-0.58(0.13)***	0.05(0.08)	-0.58(0.14)***	0.03(0.08)	-0.56(0.14)***
Hukou	0.11(0.06)ǂ	0.05(0.14)	0.10(0.06)	0.07(0.13)	0.29(0.07)***	0.02(0.13)	0.24(0.09)**	0.03(0.16)	0.13(0.09)	0.06(0.16)
SHI	Reference = no SHI									
FMS	0.36(0.14)*	-0.16(0.22)	0.36(0.13)**	-0.19(0.22)	0.79(0.18)***	-0.13(0.24)	0.79(0.17)***	-0.16(0.21)	0.78(0.17)***	-0.17(0.21)
Urban SHI	0.07(0.07)	-0.08(0.21)	0.07(0.08)	-0.07(0.19)	0.19(0.11)ǂ	-0.07(0.18)	0.21(0.10)*	-0.10(0.17)	0.23(0.10)*	-0.11(0.17)
NCMS	0.17(0.08)*	-0.13(0.19)	0.17(0.08)*	-0.14(0.18)	0.29(0.11)**	-0.19(0.17)	0.30(0.10)**	-0.20(0.16)	0.27(0.11)*	-0.22(0.16)
PHI			-0.28(0.16)ǂ	0.28(0.31)	-0.30(0.25)	0.39(0.43)	-0.20(0.18)	0.28(0.30)	-0.17(0.18)	0.28(0.30)

Utilisation					-4.23(0.09)***	1.26(0.11)***	-4.23(0.09)***	1.27(0.10)***	-4.26(0.09)***	1.27(0.10)***
Health status	-16.73(15.30)		-21.14(13.27)		-20.78(15.98)		-4.26(0.10)***		-4.25(0.10)***	
Aggregate variables										
East							0.06(0.06)	0.08(0.10)	0.01(0.07)	0.16(0.11)
Urban							0.08(0.08)	0.01(0.15)	0.04(0.08)	0.01(0.16)
Health infrastructure									-0.06(0.01)***	0.00(0.02)
Transportation									-0.03(0.01)†	0.04(0.02)†
Economic activity									0.01(0.01)	0.00(0.02)
Social services									-0.01(0.01)	0.04(0.02)*
Population									-0.08(0.03)**	-0.08(0.05)†
Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471.										
Significance values: †p≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.										

7.4 Disaggregation

In this section, the study population is disaggregated into the four subpopulations of the urban east, the rural east, the urban inland and the rural inland, as is in the last two chapters, applied to both the Heckman model and the ZINB model. Their dependent variables are summarised based on the subpopulations (Table 7.8). All three dependent variables, since they are derived from the same expenditure variable, tend to be greater in the east and urban areas than in inland and rural areas, respectively. Thus, they are the greatest in the urban east and the least in the rural inland, suggesting that those living in more affluent areas appeared to spend more out of pocket on healthcare on average.

Table 7.8 Summary of dependent variables based on subpopulations

	Urban east	*Rural east*	*Urban inland*	*Rural inland*
*Payment>50%**	0.55(0.50)	0.53(0.50)	0.47(0.50)	0.46(0.50)
*Payment>90%**	0.12(0.33)	0.11(0.31)	0.09(0.31)	0.09(0.28)
Payment (as a count)	211.08(33.3)	150.81(27.06)	185.41(22.98)	126.59(12.01)

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N=81,755.

F test shows that difference in the mean of payment (as a count) across the four subpopulations is significant (p<0.05).

*Computation is based on only healthcare users and estimates are derived from means of all imputation. Significance tests for difference are not feasible for this case.

7.4.1 The Heckman models based on subpopulations

Moving on to disaggregated Heckman models (Table 7.9), the coefficients of background variables notably vary between the four subpopulations. For two east subpopulations, nearly all demographic and socioeconomic variables are not significant. By contrast, for the two inland subpopulations, the coefficients of chronic diseases and working status reach significance in most cases. The effect of the household size is only significant in the rural inland in the model for medium financial risk, while the effect of age loses significance in all. The possible reason for this change is that, on the one hand, disaggregation reduces the sample sizes, so that statistical significance tends to fall. On the other hand, it suggests that factors affecting the financial risk vary spatially. For example, because the positive effect of chronic diseases is only significantly for the two inland subpopulations, it suggests that chronic diseases seemed more likely to trigger financial risk in the inland than in the east, due possibly to different levels of financial protection and chronic disease management between the east and the inland of the country.

Focusing on health insurance, PHI, again, fails to have a significant effect on both levels of financial risk for all subpopulations. By contrast, SHI schemes appeared to perform better than PHI. Like the outcome based on the whole population, SHI schemes' negative associations with medium financial risk are still stronger than those with high financial risk for all subpopulations. In terms of medium financial risk, SHI's associations are generally the strongest in the richest urban east and the weakest in the poorest rural inland. For the latter, only the NCMS was significantly negatively associated with the risk occurrence (OR = 0.80, 95% CI 0.68 – 0.93), not as much as it was in the rural east (OR = 0.75, 95% CI 0.60 – 0.93). However, in terms of high financial risk, only the NCMS's negative effect reaches marginal significance in the rural east (OR = 0.77, 95% CI 0.59 – 1.02) and the rural inland (OR = 0.81, 95% CI 0.64 – 1.04). This suggests that for those living and also using healthcare in rural areas, the NCMS's risk reduction was relatively comprehensive. Comparatively, the urban SHI was again less effective than other SHI schemes in all areas.

Table 7.9 The Heckman models based on subpopulations								
Population	*Urban east*		*Rural east*		*Urban inland*		*Rural inland*	
Model	*Model 18b*	*Model 18c*	*Model 19b*	*Model 19c*	*Model 20b*	*Model 20c*	*Model 21b*	*Model 21c*
Risk level	*>50%*	*>90%*	*>50%*	*>90%*	*>50%*	*>90%*	*>50%*	*>90%*
Fixed effect: coefficient (S.D.)								
Year	Reference = 2000							
2004	0.01(0.22)	0.00(0.27)	0.13(0.13)	-0.15(0.19)	0.03(0.13)	0.15(0.22)	-0.06(0.09)	-0.13(0.12)
2006	-0.01(0.21)	-0.14(0.30)	0.21(0.14)	-0.08(0.20)	-0.00(0.13)	-0.07(0.21)	-0.18(0.10) ǂ	-0.32(0.13)*
2009	0.08(0.25)	-0.00(0.32)	0.24(0.14) ǂ	-0.06(0.19)	0.13(0.13)	0.15(0.20)	-0.02(0.13)	-0.19(0.18)
2011	-0.09(0.23)	-0.10(0.31)	0.32(0.15)*	0.15(0.21)	0.00(0.16)	0.16(0.21)	-0.04(0.14)	0.01(0.17)
Age	-0.01(0.00)	-0.01(0.01)	-0.00(0.00)	-0.00(0.00)	-0.00(0.00)	-0.00(0.00)	-0.00(0.00)	-0.00(0.00)
Gender	-0.04(0.10)	-0.00(0.14)	0.01(0.07)	0.09(0.10)	-0.02(0.07)	0.04(0.10)	0.01(0.05)	0.06(0.08)
Chronic diseases	0.06(0.10)	0.06(0.13)	0.12(0.08)	0.13(0.11)	0.19(0.08)*	0.21(0.09)*	0.22(0.06)***	0.24(0.07)**
Household income	-0.01(0.05)	-0.06(0.07)	0.02(0.03)	0.00(0.05)	0.02(0.03)	0.05(0.04)	0.03(0.02)	0.05(0.04)
Household size	-0.03(0.03)	-0.03(0.05)	-0.04(0.03)	-0.03(0.03)	-0.03(0.02)	-0.04(0.03)	-0.03(0.01)**	-0.03(0.02)
Education	Reference = no or primary school							
Middle or tech	-0.07(0.12)	-0.02(0.16)	0.03(0.08)	0.02(0.11)	-0.01(0.08)	0.00(0.13)	0.12(0.06)*	0.12(0.08)
University	-0.22(0.20)	0.04(0.26)	-0.12(0.20)	0.05(0.27)	-0.06(0.13)	-0.02(0.20)	0.32(0.23)	0.32(0.28)
Working	-0.10(0.14)	-0.16(0.21)	-0.14(0.08) ǂ	-0.12(0.13)	-0.18(0.11)	-0.26(0.13)*	-0.20(0.06)**	-0.30(0.08)***
Hukou	0.09(0.21)	0.20(0.26)	0.06(0.12)	0.13(0.14)	-0.02(0.11)	0.07(0.15)	-0.04(0.09)	0.06(0.11)
SHI	Reference = no SHI							
FMS	-0.47(0.18)*	-0.13(0.23)	-0.39(0.19)*	-0.45(0.31)	-0.41(0.10)***	-0.18(0.18)	-0.19(0.22)	-0.18(0.27)
Urban SHI	-0.29(0.15) ǂ	-0.05(0.23)	-0.30(0.13)*	-0.15(0.19)	-0.20(0.10) ǂ	-0.10(0.11)	-0.03(0.13)	0.07(0.18)
NCMS	-0.48(0.22)*	-0.19(0.32)	-0.30(0.12)*	-0.27(0.14) ǂ	-0.29(0.16) ǂ	-0.30(0.22)	-0.22(0.08)**	-0.21(0.12) ǂ

PHI	-0.05(0.19)	-0.11(1.16)	-0.09(0.34)	0.05(0.38)	0.16(0.28)	0.11(0.38)	0.10(0.41)	-0.66(1.82)
Aggregate variables								
Health infrastructure	-0.02(0.03)	-0.01(0.04)	0.02(0.02)	0.00(0.02)	0.02(0.02)	0.02(0.02)	0.01(0.01)	0.00(0.01)
Transportation	-0.00(0.02)	-0.02(0.03)	0.05(0.02)**	0.04(0.03)	0.02(0.02)	-0.00(0.02)	0.01(0.01)	0.02(0.02)
Economic activity	-0.01(0.03)	-0.01(0.04)	-0.01(0.02)	0.01(0.02)	0.02(0.02)	0.00(0.03)	0.01(0.01)	0.01(0.01)
Social services	0.01(0.02)	-0.00(0.02)	0.02(0.02)	0.02(0.02)	0.01(0.01)	0.01(0.02)	0.02(0.01)	0.02(0.02)
Population	0.06(0.05)	0.03(0.07)	-0.01(0.04)	-0.01(0.05)	-0.03(0.03)	-0.04(0.04)	-0.04(0.02) ǂ	-0.06(0.03) ǂ

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471 (Urban east: n=9265; Rural east: n=17210; Urban inland: n=19400; Rural inland: n=34870).

Significance values: ǂp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.

The outcome of the first equation on healthcare utilisation is not presented.

7.4.2 The ZINB models based on subpopulations

Like the Heckman models on the subpopulations, in the ZINB models (Table 7.10), the chronic diseases variable only significantly correlates to an increase in the amount of OOP payments for the two inland subpopulations, while it is significantly negatively associated with the occurrence of zero OOP spending for all. This corroborates the inference from the Heckman models that chronic diseases were more associated with increased financial risk in the poorer inland than in the east. Likewise, the significantly negative effect of the year 2006 on the amount of OOP payments only happens in the rural inland (Table 7.10: Model 25b) as it does in the Heckman model on high risk (Table 7.9: Model 21c). The negative effect of working status on the amount of OOP payments is generally similar between the two types of models as well: it is mainly significant in the rural inland and insignificant in the urban east. All in all, these suggest that in terms of control variables, the Heckman model and the ZINB model are basically consistent.

In terms of SHI, the FMS is significantly positively correlated to the occurrence of zero payment in all but the rural inland (urban east: OR = 3.25, 95% CI 1.81 – 7.01; rural east: OR = 2.09, 95% CI 1.11 – 4.56; urban inland: OR = 1.79, 95% CI 1.17 – 2.57; rural inland: OR = 1.38, 95% CI 0.61 – 3.12). Comparatively, the urban SHI again has the worst performance of all. The NCMS only has such effect in rural areas, significant in the rural east (OR = 1.39, 95% CI 1.02 – 1.88) and marginally significant in the rural inland (OR = 1.38, 95% CI 1.00 – 1.91) (Table 7.10: Model 23a and 25a). Regarding the effect on the amount of OOP payments, the negative effect of the NCMS is marginally significant in the rural east, but insignificant in the rural inland (Table 7.10: Model 23b and 25b). These suggest that the NCMS might increase the probability of zero OOP payment (by offering free basic care) and tend to directly reduce OOP payments (by effectively compensating the costs of advanced care) in the rural east, but only increase the probability of zero OOP payment in the rural inland.

PHI still has no significant association with either the occurrence of zero OOP payment or the amount of OOP payments in all areas. In terms of coefficient magnitude, there is a pattern that PHI has greater positive effects on the amount of OOP payments in the east than the inland. However, the standard deviations for these effects are all so high that they prevent them from reaching statistical significance. By comparison, the standard deviations for effects of SHI schemes are less than PHI's in most cases, which is also true for the Heckman models. This suggests that it is common in China that PHI's financial protection is more unequal than SHI's among individuals.

Table 7.10 The ZINB models based on subpopulations								
Population	*Urban east*		*Rural east*		*Urban inland*		*Rural inland*	
Model	*Model 22a*	*Model 22b*	*Model 23a*	*Model 23b*	*Model 24a*	*Model 24b*	*Model 25a*	*Model 25b*
Equation	*%Zero*	*Count*	*%Zero*	*Count*	*%Zero*	*Count*	*%Zero*	*Count*
Fixed effect: coefficient (S.D.)								
Year	Reference = 2000							
2004	-1.82(0.36)***	-0.16(0.63)	-2.17(0.24)***	-0.22(0.47)	-1.45(0.22)***	0.07(0.38)	-1.62(0.15)***	-0.17(0.29)
2006	-1.84(0.44)***	-0.32(0.61)	-1.86(0.27)***	-0.4(0.51)	-1.32(0.21)***	-0.17(0.37)	-1.44(0.17)***	-0.68(0.29)*
2009	-1.6(0.41)***	-0.2(0.59)	-1.98(0.27)***	-0.18(0.46)	-1.3(0.24)***	0.21(0.39)	-1.43(0.23)***	-0.52(0.38)
2011	-1.07(0.47)*	-0.29(0.58)	-1.53(0.29)***	0.25(0.51)	-0.93(0.24)***	0.47(0.37)	-1.56(0.25)***	-0.1(0.41)
Age	0.00(0.01)	0.00(0.01)	0.00(0.01)	0.00(0.01)	-0.01(0)	0.00(0.01)	0.00(0.00)	0.00(0.01)
Gender	0.11(0.14)	0.07(0.23)	0.30(0.12)*	0.19(0.17)	0.2(0.13)	0.14(0.21)	0.11(0.09)	0.13(0.13)
Chronic diseases	-0.33(0.16)*	0.34(0.24)	-0.79(0.14)***	0.32(0.19)ǂ	-0.38(0.13)**	0.53(0.17)**	-0.48(0.15)**	0.6(0.14)**
Household income	0.06(0.08)	0.02(0.11)	-0.01(0.06)	0.06(0.08)	0.01(0.06)***	0.01(0.07)	-0.05(0.05)	0.06(0.06)
Household size	0.07(0.07)	-0.04(0.09)	0.12(0.05)*	0(0.06)	0.05(0.04)	-0.05(0.05)	0(0.03)	-0.05(0.04)
Education	Reference = no or primary school							
Middle or tech	0.08(0.22)	0.07(0.3)	0.01(0.13)	-0.01(0.21)	0.16(0.15)	-0.1(0.22)	0.04(0.11)	0.15(0.15)
University	-0.04(0.32)	-0.29(0.38)	-0.12(0.34)	0.25(0.49)	0.04(0.22)	-0.02(0.38)	-0.11(0.42)	0.51(0.41)
Working	0.00(0.17)	-0.40(0.32)	0.07(0.14)	-0.55(0.19)**	0.10(0.14)	-0.39(0.26)	-0.01(0.12)	-0.64(0.17)***
Hukou	0.05(0.28)	0.36(0.53)	-0.02(0.16)	0.43(0.24)ǂ	-0.01(0.2)	0.08(0.28)	0.09(0.16)	-0.1(0.21)
SHI	Reference = no SHI							
FMS	1.18(0.36)**	-0.08(0.4)	0.74(0.37)*	-0.67(0.5)	0.58(0.22)*	-0.05(0.34)	0.32(0.45)	-0.3(0.41)
Urban SHI	0.07(0.21)	-0.1(0.33)	0.39(0.2)ǂ	-0.18(0.31)	0.21(0.14)	-0.21(0.21)	0.11(0.26)	0.15(0.32)
NCMS	0.42(0.39)	-0.45(0.55)	0.34(0.15)*	-0.53(0.25)ǂ	0.36(0.27)	0.14(0.41)	0.32(0.17)ǂ	-0.12(0.21)

PHI	-0.63(0.39)	0.35(0.78)	0.11(0.46)	0.38(0.66)	-0.24(0.42)	0.09(0.66)	-0.01(0.7)	0.06(0.86)
Utilisation	-3.61(0.26)***	1.32(0.24)***	-4.23(0.19)***	1.39(0.17)***	-3.84(0.17)***	1.4(0.18)***	-4.71(0.13)***	1.1(0.16)***
Health status	-3.97(0.27)***		-4.22(0.17)***		-4.31(0.21)***		-4.34(0.13)***	
Aggregate variables								
Health infrastructure	-0.08(0.05)	0.02(0.05)	-0.12(0.03)***	-0.01(0.04)	-0.07(0.03)*	-0.01(0.04)	-0.03(0.02)	0.01(0.03)
Transportation	0.03(0.04)	-0.04(0.06)	-0.05(0.03)ǂ	0.07(0.04)ǂ	-0.03(0.03)	-0.01(0.06)	-0.02(0.02)	0.05(0.03)
Economic activity	-0.03(0.05)	-0.05(0.08)	0.02(0.03)	0.01(0.04)	0(0.03)	-0.04(0.04)	0.02(0.02)	0.01(0.03)
Social services	0.01(0.03)	0(0.04)	-0.04(0.03)ǂ	0(0.03)	0.01(0.02)	0.06(0.03)*	-0.03(0.03)	0.06(0.03)ǂ
Population	-0.17(0.06)*	0(0.13)	-0.03(0.06)	0.01(0.09)	-0.07(0.05)	-0.1(0.08)	-0.07(0.04)ǂ	-0.08(0.06)

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471 (Urban east: n=9265; Rural east: n=17210; Urban inland: n=19400; Rural inland: n=34870).

Significance values: ǂp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.

The outcome of the first equation on utilisation is not presented.

7.5 Temporal variation of financial protection

As in the last two chapters, this section is developed to check if insurance financial protection has changed over time, in case valuable information is hidden by pooling data. Likewise, the examinations primarily focus on differences between the two ends of this study period, i.e. 2000 and 2011, and other years, respectively.

Between the year 2000 and other years afterwards, for the Heckman model based on the whole population (Table 7.11), the interactions between SHI schemes and the time transition, are all not significant, while there is a marginally significantly positive interaction between PHI and the time transition in the model on medium financial risk (OR = 1.35, 95% CI 0.96 – 1.90). This suggests that while SHI's financial protection remained unchanged, enrolment into PHI tended to become more associated with the occurrence of medium financial risk since 2004, compared to 2000. For subpopulations, PHI showed the same trend across most areas, except the poorest rural inland, though insignificant. Additionally, the NCMS has a marginally significantly positive interaction in the rural inland for high financial risk (OR = 30.17, 95% CI 0.65 – 1405.54), suggesting that its correlation with lower risk weakened since 2004 compared to 2000. Overall, the Chow tests do not find any significant difference in the effects of PHI and SHI between the two periods.[39]

The ZINB models have a similar profile where most of these interactions are insignificant (Table 7.12). A difference is that for the whole population and the urban inland , the time transition has a significantly positive interaction with the urban SHI (OR = 2.31, 95% CI 1.33 – 4.00; OR = 2.13, 95% CI 1.15 – 3.95, respectively), and a marginally significantly positive interaction with the FMS, on the occurrence of zero OOP payment (OR = 2.22, 95% CI 0.93 – 5.34; OR = 1.98, 95% CI 0.95 – 4.13). This suggests that since 2004 the FMS and the urban SHI overall have become more likely

[39] The F test tests the main effect of the time transition and their interactions with health insurance schemes being equal to 0.

to ensure zero OOP payment, particularly in the urban inland. In addition, consistent with the results of the Heckman models, though insignificant, PHI demonstrates the trend of being less associated with zero OOP payment since 2004 and more associated with an increased amount of OOP payments, and this trend is also relatively weak in the rural inland. The Chow tests find a significant change in the coefficients of PHI and SHI between the two periods on the occurrence of zero OOP payment for all the populations but no significant change on the amount of OOP payments.

Between the years 2000-2009 and the year 2011, both the Heckman models and the ZINB models do not find any significant interaction between a health insurance scheme and the time transition, based on either the total population or the disaggregated populations (Table 7.13 and 7.14). The Chow tests do not find any significant difference as well. This suggests that the policy change during this period, when the 2009 health reforms theoretically promoted SHI coverage, did not significantly influence financial protection of SHI schemes and PHI.

Taking together, the temporal changes in financial protection of PHI and SHI were generally moderate. For PHI, although there are some patterns that show its effects might change between 2000 and 2004 and afterwards, these are not statistically significant at the 0.05 level. Neither are SHI schemes in most cases. The Chow test of overall different effects of health insurance schemes is only significant on the occurrence of zero OOP payment. There is no dramatic reversal like what occurred to the correlation between SHI enrolment and PHI enrolment (Section 5.4). The method of handling longitudinal data, i.e. estimation-based pooled data, should be acceptable here.

Table 7.11 Difference of SHI and PHI's effects between 2000 and 2004-2011 – the Heckman models										
Population	*Total*		*Urban east*		*Rural east*		*Urban inland*		*Rural inland*	
Model	*Model 26a*	*Model 26b*	*Model 27a*	*Model 26b*	*Model 28a*	*Model 28b*	*Model 29a*	*Model 29b*	*Model 30a*	*Model 30b*
Risk level	*>50%*	*>90%*	*>50%*	*>90%*	*>50%*	*>90%*	*>50%*	*>90%*	*>50%*	*>90%*
Fixed effect: coefficient (S.D.)										
Post-2000‡	-0.03(0.07)	-0.13(0.09)	0.06(0.31)	0.04(0.38)	0.17(0.16)	-0.16(0.20)	-0.08(0.14)	-0.01(0.20)	-0.11(0.09)	-0.21(0.12)ᵼ
SHI	Reference = no SHI									
FMS	-0.34(0.08)***	-0.18(0.12)	-0.47(0.19)*	-0.12(0.24)	-0.35(0.18)ᵼ	-0.36(0.29)	-0.35(0.11)**	-0.17(0.18)	-0.19(0.23)	-0.17(0.29)
Urban SHI	-0.16(0.06)**	-0.02(0.08)	-0.33(0.15)*	-0.10(0.23)	-0.22(0.13)	-0.01(0.18)	-0.16(0.09)ᵼ	-0.05(0.11)	0.03(0.13)	0.16(0.16)
NCMS	-0.20(0.04)***	-0.15(0.06)	-0.46(0.20)*	-0.20(0.31)	-0.24(0.11)*	-0.16(0.14)	-0.26(0.15)ᵼ	-0.25(0.23)	-0.18(0.06)**	-0.13(0.08)ᵼ
Post-2000×FMS	0.06(0.19)	-0.10(0.24)	-0.01(0.42)	-0.12(0.51)	-0.34(0.54)	-0.35(0.70)	0.22(0.28)	-0.06(0.47)	-0.28(0.59)	-0.44(0.57)
Post-2000×Urban SHI	-0.10(0.20)	0.08(0.26)	-0.69(0.51)	-0.40(0.53)	-0.14(0.57)	-0.19(0.69)	0.22(0.35)	0.68(1.44)	0.18(0.61)	2.89(2.44)
Post-2000×NCMS	0.15(0.18)	0.01(0.25)	-0.08(0.58)	-0.53(0.65)	-0.09(0.27)	0.19(0.42)	0.49(0.58)	2.57(2.36)	0.59(0.58)	3.41(1.85)ᵼ
PHI	0.14(0.11)	0.27(0.14)ᵼ	0.11(0.24)	0.20(0.30)	0.13(0.17)	0.34(0.22)	0.15(0.21)	0.23(0.23)	0.04(0.28)	0.12(0.39)
Post-2000×PHI	0.30(0.18)ᵼ	0.38(0.25)	0.44(0.41)	0.31(0.51)	0.40(0.36)	0.43(0.54)	0.19(0.33)	0.43(0.54)	-0.27(0.63)	0.05(0.76)

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471 (Urban east: n=9265; Rural east: n=17210; Urban inland: n=19400; Rural inland: n=34870).

Significance values: ᵼp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.

Adjusted for demographic, socioeconomic and aggregate variables like those in Model 8.

The outcomes of the first equation on healthcare utilisation are not presented.

‡ Post-2000 refers to the 2004, 2006, 2009 and 2011 waves of data of the CHNS.

The Chow tests find no significant change in the coefficients of PHI and SHI schemes between the two periods on the two levels of financial risk for all the populations.

Table 7.12 Difference of SHI and PHI's effects between 2000 and 2004-2011 – the ZINB models

Population	*Total*		*Urban east*		*Rural east*		*Urban inland*		*Rural inland*	
Model	*Model 31a*	*Model 31b*	*Model 32a*	*Model 32b*	*Model 33a*	*Model 33b*	*Model 34a*	*Model 34b*	*Model 35a*	*Model 35b*
Equation	*%Zero*	*Count*	*%Zero*	*Count*	*%Zero*	*Count*	*%Zero*	*Count*	*%Zero*	*Count*
Fixed effect: coefficient (S.D.)										
Post-2000‡	-1.62(0.10)***	-0.29(0.23)	-1.89(0.38)***	-0.25(0.78)	-2.06(0.28)***	-0.34(0.54)	-1.46(0.19)***	-0.12(0.38)	-1.53(0.14)***	-0.34(0.29)
SHI	Reference = no SHI									
FMS	0.85(0.19)***	-0.09(0.22)	1.28(0.36)	-0.08(0.40)	0.78(0.36)*	-0.60(0.52)	0.65(0.23)**	0.03(0.32)	0.30(0.44)	-0.31(0.43)
Urban SHI	0.36(0.11)**	-0.02(0.15)	0.36(0.18)†	-0.13(0.35)	0.55(0.20)**	-0.01(0.30)	0.38(0.14)*	-0.04(0.21)	0.13(0.25)	0.17(0.32)
NCMS	0.40(0.09)***	-0.15(0.14)	0.52(0.36)	-0.41(0.56)	0.50(0.15)**	-0.43(0.23)†	0.51(0.26)†	-0.35(0.44)	0.37(0.12)**	-0.13(0.14)
Post-2000×FMS	0.68(0.37)†	0.08(0.72)	0.23(0.91)	0.06(1.07)	0.45(1.68)	-0.34(1.32)	0.80(0.44)†	0.09(0.95)	-0.19(1.49)	-0.50(0.94)
Post-2000×Urban SHI	0.84(0.28)**	0.26(0.73)	0.94(0.63)	0.01(0.95)	0.67(0.85)	0.51(1.20)	0.76(0.31)*	0.33(0.93)	0.85(0.90)	1.32(1.19)
Post-2000×NCMS	-0.57(0.68)	-0.14(0.81)	-0.24(1.42)	-1.00(1.50)	0.22(0.64)	0.41(0.83)	-0.46(1.58)	0.90(1.60)	-0.96(1.45)	1.39(0.98)
PHI	-0.22(0.21)	0.40(0.35)	-0.36(0.34)	0.32(0.51)	-0.03(0.27)	0.35(0.41)	-0.21(0.34)	0.50(0.61)	-0.25(0.51)	0.07(0.67)
Post-2000×PHI	-0.66(0.42)	0.60(0.62)	-0.73(0.87)	0.53(1.32)	-1.18(1.52)	0.62(1.01)	-0.63(0.52)	1.03(0.79)	-0.74(1.12)	0.13(0.95)

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471 (Urban east: n=9265; Rural east: n=17210; Urban inland: n=19400; Rural inland: n=34870).

Significance values: †p≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.

Adjusted for demographic, socioeconomic and aggregate variables like those in Model 17.

‡ Post-2000 refers to the 2004, 2006, 2009 and 2011 waves of data of the CHNS.

The Chow tests find a significant change in the coefficients of PHI and SHI schemes between the two periods on the occurrence of zero OOP payment for all the populations (p<0.001 for all) but no significant change on the amount of OOP payments for all the populations.

Table 7.13 Difference of SHI and PHI's effects between 2000-2009 and 2011 – the Heckman models

Population	*Total*		*Urban east*		*Rural east*		*Urban inland*		*Rural inland*	
Model	*Model 36a*	*Model 36b*	*Model 37a*	*Model 36b*	*Model 38a*	*Model 38b*	*Model 39a*	*Model 39b*	*Model 40a*	*Model 40b*
Risk level	*>50%*	*>90%*	*>50%*	*>90%*	*>50%*	*>90%*	*>50%*	*>90%*	*>50%*	*>90%*
Fixed effect: coefficient (S.D.)										
Post-2009‡	0.14(0.15)	0.30(0.21)	0.18(0.46)	0.11(0.55)	0.06(0.43)	0.60(0.52)	-0.01(0.21)	0.13(0.25)	0.32(0.31)	0.40(0.39)
SHI	Reference = no SHI									
FMS	-0.38(0.08)***	-0.20(0.10)ǂ	-0.47(0.18)**	-0.12(0.21)	-0.39(0.17)*	-0.42(0.27)	-0.42(0.11)***	-0.20(0.17)	-0.22(0.22)	-0.11(0.25)
Urban SHI	-0.13(0.07)ǂ	-0.05(0.09)	-0.26(0.15)ǂ	-0.05(0.21)	-0.20(0.14)	-0.11(0.21)	-0.15(0.10)	-0.05(0.12)	-0.03(0.17)	0.03(0.19)
NCMS	-0.23(0.05)***	-0.21(0.07)**	-0.50(0.20)*	-0.15(0.29)	-0.24(0.10)*	-0.22(0.13)	-0.33(0.17)ǂ	-0.19(0.27)	-0.18(0.06)**	-0.23(0.10)*
Post-2009×FMS	-0.02(0.24)	-0.05(0.33)	-0.46(0.65)	-0.85(1.74)	0.64(0.65)	0.12(0.74)	0.12(0.34)	0.14(0.43)	0.32(0.67)	-0.16(0.73)
Post-2009×Urban SHI	-0.20(0.17)	-0.20(0.23)	-0.30(0.46)	-0.18(0.56)	-0.01(0.46)	-0.31(0.54)	-0.11(0.21)	-0.13(0.28)	-0.17(0.39)	-0.14(0.50)
Post-2009×NCMS	-0.11(0.16)	-0.15(0.22)	-0.14(0.59)	-0.03(0.80)	0.09(0.44)	-0.41(0.53)	0.04(0.29)	-0.33(0.47)	-0.34(0.31)	-0.21(0.41)
PHI	0.01(0.09)	0.18(0.12)	-0.02(0.20)	0.21(0.23)	0.05(0.18)	0.36(0.23)	-0.02(0.14)	-0.04(0.23)	-0.00(0.24)	0.05(0.35)
Post-2009×PHI	-0.01(0.21)	-0.08(0.24)	-0.40(0.50)	-1.19(1.91)	-0.14(0.31)	-0.43(0.42)	0.04(0.40)	0.40(0.44)	0.23(0.61)	-0.44(1.57)

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471 (Urban east: n=9265; Rural east: n=17210; Urban inland: n=19400; Rural inland: n=34870).

Significance values: ǂp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.

Adjusted for demographic, socioeconomic and aggregate variables like those in Model 8.

The outcomes of the first equation on healthcare utilisation are not presented.

‡ Post-2009 refers to the 2011 data of the CHNS.

The Chow tests find no significant change in the coefficients of PHI and SHI schemes between the two periods on the two levels of financial risk for all the populations.

Table 7.14 Difference of SHI and PHI's effects between 2000-2009 and 2011 – the ZINB models										
Population	*Total*		*Urban east*		*Rural east*		*Urban inland*		*Rural inland*	
Model	*Model 41a*	*Model 41b*	*Model 42a*	*Model 42b*	*Model 43a*	*Model 43b*	*Model 44a*	*Model 44b*	*Model 45a*	*Model 45b*
Equation	*%Zero*	*Count*	*%Zero*	*Count*	*%Zero*	*Count*	*%Zero*	*Count*	*%Zero*	*Count*
Fixed effect: coefficient (S.D.)										
Post-2009‡	-0.08(0.24)	0.72(0.39) ᵼ	0.52(0.65)	0.50(1.00)	0.18(0.57)	1.07(0.86)	0.04(0.29)	0.65(0.46)	-0.63(0.49)	0.32(0.73)
SHI	Reference = No SHI									
FMS	0.73(0.17)***	-0.20(0.26)	1.31(0.33)***	-0.05(0.37)	0.72(0.35)*	-0.67(0.50)	0.52(0.21)*	-0.11(0.36)	0.30(0.41)	-0.39(0.44)
Urban SHI	0.05(0.11)	-0.12(0.16)	0.09(0.19)	-0.07(0.31)	0.25(0.20)	-0.21(0.30)	0.12(0.14)	-0.05(0.21)	0.06(0.29)	-0.10(0.34)
NCMS	0.13(0.09)	-0.27(0.15) ᵼ	0.44(0.39)	-0.34(0.58)	0.09(0.14)	-0.52(0.21)*	0.38(0.34)	0.39(0.54)	0.12(0.13)	-0.33(0.17) ᵼ
Post-2009×FMS	0.83(0.59)	0.13(0.71)	0.21(1.26)	-0.97(1.46)	1.09(1.62)	0.02(1.23)	0.92(0.74)	0.34(0.90)	0.52(1.21)	0.54(1.16)
Post-2009×Urban SHI	0.49(0.30)	-0.34(0.44)	0.06(0.68)	-0.69(0.96)	0.19(0.61)	-0.44(0.96)	0.39(0.36)	-0.46(0.56)	0.31(0.57)	0.24(0.82)
Post-2009×NCMS	0.18(0.25)	-0.37(0.41)	-0.18(0.95)	-0.49(1.27)	0.23(0.63)	-0.72(0.91)	-0.03(0.58)	-0.70(0.80)	0.59(0.49)	0.09(0.73)
PHI	0.19(0.18)	0.34(0.34)	0.16(0.30)	0.38(0.46)	0.30(0.27)	0.41(0.47)	0.20(0.24)	0.13(0.53)	0.20(0.52)	-0.03(0.51)
Post-2009×PHI	-0.14(0.43)	-0.36(0.71)	-0.32(0.91)	-0.71(1.01)	-0.23(0.66)	-0.74(0.70)	0.01(0.72)	0.12(0.87)	-0.26(0.89)	-0.20(1.16)

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471 (Urban east: n=9265; Rural east: n=17210; Urban inland: n=19400; Rural inland: n=34870).

Significance values: ᵼp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.

Adjusted for demographic, socioeconomic and aggregate variables like those in Model 17.

‡ Post-2009 refers to the 2011 data of the CHNS.

The Chow tests find no significant change in the coefficients of PHI and SHI schemes between the two periods in two equations for all the populations.

7.6 The dual insurance effect on financial protection

Examining the interactions between SHI schemes and PHI to explore the dual insurance effect, neither the Heckman models nor the ZINB models find any significant interactions between any SHI scheme and PHI, based on either the total population or the subpopulations after disaggregation (Table 7.15 and 7.16). Moreover, adding the interactions has no notable impact on the main effects of SHI schemes and PHI.

Furthermore, for the ZINB model, a three-way interaction among PHI, SHI and utilisation is made to explore whether there is a difference in health insurance's effects between healthcare users and non-users.[40] Again, a simplified binary variable indicating membership of any SHI scheme is used as a substitute for the categorical SHI variable, for the same reason of increasing observations for categories that has been stated in the last chapter (Section 6.6). As a result, neither the two-way interaction between SHI and PHI nor the three-way interaction between SHI, PHI and utilisation is significant for all populations (Table 7.17).

Taken all together, this suggests that there was no mutually additional (or detrimental) effect on financial protection for those covered by both SHI and PHI, regardless of utilisation. This result implies that in China the compensation procedures of SHI and PHI may be so separate from each other that they have little impact on each other's effect on OOP payments.

Interestingly, in these three-way-interaction models on the occurrence of zero OOP payment, both the interactions between SHI and utilisation (OR = 3.96, 95% CI 2.54 – 6.19), and between PHI and utilisation (OR =5.63, 95% CI 1.12 – 28.20), are significantly positive for the whole population (Table 7.17: Model 46a). Taking the

[40] The three-way interaction does not apply to Heckman model, because its second equation has been based on healthcare users already.

main effects and interactions together, these indicate that among healthcare users SHI enrolees and PHI enrolees were positively associated with the occurrence of zero OOP payment compared to those without SHI and those without PHI, respectively (SHI: OR = 4.85, 95% CI 3.07 – 7.65; PHI: OR = 3.89, 95% CI 0.80 – 18.87, with marginal significance $p<0.1$). For SHI, the positive interaction also applies to all disaggregated subpopulations, though they are significant only for the two inland ones. This supports a previous inference (in Section 7.3.2) that SHI offered some basic services for free to users, especially in the inland areas. For PHI, however, the interactions for the subpopulations are too mixed to have a pattern, with none being significant, possibly because the coverage foci of PHI policies are not as uniform as SHI policies and also influenced by local healthcare systems.

Table 7.15 The interactions between SHI schemes and PHI – the Heckman models										
Population	*Total*		*Urban east*		*Rural east*		*Urban inland*		*Rural inland*	
Model	*Model 36a*	*Model 36b*	*Model 37a*	*Model 36b*	*Model 38a*	*Model 38b*	*Model 39a*	*Model 39b*	*Model 40a*	*Model 40b*
Risk level	*>50%*	*>90%*	*>50%*	*>90%*	*>50%*	*>90%*	*>50%*	*>90%*	*>50%*	*>90%*
Fixed effect: coefficient (S.D.)										
SHI	Reference = no SHI									
FMS	-0.37(0.08)***	-0.20(0.11) ƚ	-0.47(0.18)*	-0.13(0.23)	-0.39(0.19)*	-0.45(0.31)	-0.41(0.10)***	-0.18(0.18)	-0.19(0.22)	-0.18(0.27)
Urban SHI	-0.18(0.06)**	-0.06(0.09)	-0.29(0.15) ƚ	-0.05(0.23)	-0.30(0.13)*	-0.15(0.19)	-0.20(0.10) ƚ	-0.10(0.11)	-0.03(0.13)	0.07(0.18)
NCMS	-0.22(0.05)***	-0.20(0.07)**	-0.48(0.22)*	-0.19(0.32)	-0.30(0.12)*	-0.27(0.14) ƚ	-0.29(0.16) ƚ	-0.30(0.22)	-0.22(0.08)**	-0.21(0.12)ƚ
PHI	0.11(0.17)	0.14(0.23)	-0.00(0.43)	-0.11(1.16)	-0.09(0.34)	0.05(0.38)	0.16(0.28)	0.11(0.38)	0.10(0.41)	-0.66(1.82)
FMS×PHI	-0.12(0.25)	-0.00(0.33)	-0.19(0.54)	0.25(1.24)	0.30(0.62)	0.45(0.67)	-0.16(0.35)	-0.13(0.61)	0.27(0.83)	1.51(2.02)
Urban SHI×PHI	-0.06(0.21)	-0.07(0.32)	0.04(0.53)	0.07(1.35)	0.19(0.48)	0.25(0.62)	-0.18(0.35)	-0.04(0.50)	0.17(0.59)	-0.34(2.52)
NCMS×PHI	-0.14(0.24)	0.10(0.30)	0.12(0.63)	0.60(1.23)	0.12(0.40)	0.13(0.48)	-0.98(1.28)	-2.33(2.62)	-0.24(0.53)	0.66(1.91)
Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471 (Urban east: n=9265; Rural east: n=17210; Urban inland: n=19400; Rural inland: n=34870). Significance values: ƚp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001. Adjusted for demographic, socioeconomic and aggregate variables like those in Model 8; The outcomes of the equation on healthcare utilisation are not presented.										

Table 7.16 The interactions between SHI schemes and PHI – the ZINB models										
Population	*Total*		*Urban east*		*Rural east*		*Urban inland*		*Rural inland*	
Model	*Model 41a*	*Model 41b*	*Model 42a*	*Model 42b*	*Model 43a*	*Model 43b*	*Model 44a*	*Model 44b*	*Model 45a*	*Model 45b*
Equation	*%Zero*	*Count*	*%Zero*	*Count*	*%Zero*	*Count*	*%Zero*	*Count*	*%Zero*	*Count*
Fixed effect: coefficient (S.D.)										
SHI	Reference = no SHI									
FMS	0.79(0.18)***	-0.14(0.24)	1.18(0.36)**	-0.08(0.4)	0.74(0.37)*	-0.67(0.5)	0.58(0.22)*	-0.05(0.34)	0.32(0.45)	-0.30(0.41)
Urban SHI	0.23(0.11)*	-0.08(0.18)	0.07(0.21)	-0.10(0.33)	0.39(0.2) ƚ	-0.18(0.31)	0.21(0.14)	-0.21(0.21)	0.11(0.26)	0.15(0.32)

NCMS	0.26(0.11)*	-0.20(0.17)	0.42(0.39)	-0.45(0.55)	0.34(0.15)*	-0.53(0.25)ᵼ	0.36(0.27)	0.14(0.41)	0.32(0.17)ᵼ	-0.12(0.21)
PHI	-0.25(0.25)	0.38(0.43)	-0.63(0.39)	0.35(0.78)	0.11(0.46)	0.38(0.66)	-0.24(0.42)	0.09(0.66)	-0.01(0.7)	0.06(0.86)
FMS×PHI	-0.03(0.40)	-0.33(0.90)	0.82(1.01)	-0.34(1.26)	0.54(1.11)	0.02(0.95)	-0.12(0.61)	-0.1(1.15)	-0.04(1.03)	0.14(1.21)
Urban SHI×PHI	0.10(0.33)	-0.28(0.61)	0.66(0.67)	-0.44(0.99)	-0.36(0.79)	-0.08(1.05)	0.32(0.51)	0.22(0.8)	-0.63(0.98)	-0.66(1.13)
NCMS×PHI	0.29(0.39)	0.02(0.65)	0.76(1.17)	0.56(1.35)	-0.20(0.65)	-0.26(0.69)	0.14(1.27)	-0.83(1.8)	0.20(1.09)	-0.11(1.07)

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471 (Urban east: n=9265; Rural east: n=17210; Urban inland: n=19400; Rural inland: n=34870).
Significance values: ᵼp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.
Adjusted for demographic, socioeconomic and aggregate variables like those in Model 17.

Table 7.17 The three-way interaction among SHI, PHI and utilisation – the ZINB models

Population	*Total*		*Urban east*		*Rural east*		*Urban inland*		*Rural inland*	
Model	*Model 46a*	*Model 46b*	*Model 47a*	*Model 47b*	*Model 48a*	*Model 48b*	*Model 49a*	*Model 49b*	*Model 50a*	*Model 50b*
Equation	*%Zero*	*Count*	*%Zero*	*Count*	*%Zero*	*Count*	*%Zero*	*Count*	*%Zero*	*Count*
Fixed effect: coefficient (S.D.)										
Utilisation	-5.28(0.20)***	1.33(0.17)***	-4.64(0.68)***	1.50(0.40)***	-4.92(0.49)***	1.36(0.36)***	-4.92(0.44)***	1.40(0.24)***	-5.59(0.29)***	1.25(0.26)***
SHI	0.20(0.09)*	-0.09(0.20)	0.21(0.23)	0.01(0.46)	0.35(0.15)*	-0.44(0.39)	0.20(0.14)	-0.13(0.28)	0.10(0.16)	0.11(0.33)
PHI	-0.37(0.24)	0.15(0.65)	-0.68(0.40)ᵼ	0.46(1.03)	-0.03(0.45)	0.06(1.09)	-0.34(0.41)	-0.13(0.76)	-0.24(0.72)	-0.54(1.46)
PHI×SHI	0.20(0.28)	-0.14(0.95)	0.78(0.60)	-0.80(1.32)	-0.11(0.58)	-0.26(1.26)	0.20(0.46)	0.45(1.16)	-0.12(0.81)	-0.21(1.51)
SHI×utilisation	1.38(0.23)***	-0.11(0.20)	1.25(0.76)	-0.25(0.51)	0.79(0.51)	0.01(0.42)	1.44(0.49)**	0.02(0.35)	1.37(0.32)***	-0.27(0.34)
PHI×utilisation	1.73(0.81)*	0.25(0.99)	-3.26(7.99)	-0.21(1.59)	1.72(1.54)	0.36(1.24)	0.71(4.29)	0.28(1.12)	-0.38(44.63)	0.64(1.81)
PHI×SHI×utilisation	-0.52(0.98)	0.09(1.18)	4.11(8.20)	0.90(1.79)	-1.12(1.85)	0.15(1.60)	0.64(4.45)	-0.38(1.44)	1.13(44.62)	0.18(1.92)

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471 (Urban east: n=9265; Rural east: n=17210; Urban inland: n=19400; Rural inland: n=34870).
Significance values: ᵼp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.
Adjusted for demographic, socioeconomic and aggregate variables like those in Model 17.

7.7 The contextual effect of health insurance

To explore the contextual financial impacts of health insurance, the SHI prevalence level and the PHI prevalence level, which indicate the percentage of SHI enrolees and PHI enrolees in a community, respectively, are introduced to both the Heckman and the ZINB models. Moreover, the utilisation level as the percentage of healthcare users in the community is controlled for. Admittedly, without the community level in the model, the estimation, especially the standard error, is likely to be compromised (Jones et al., 2012), especially involving the group-mean variables like these contextual variables (Krull and MacKinnon, 2001). However, this still deserves to be tried but interpreted with caution, since the outcome may help to understand the impacts of health insurance on equity.

For both the Heckman models and the ZINB models, most coefficients of the SHI prevalence level and the PHI prevalence level are not significant (Table 7.18 and 7.19), except in the urban east where the PHI prevalence level is significantly positively associated with the occurrence of zero OOP payment in the community (OR = 15.46, 95% CI 2.30 – 103.86) (Table 7.19: Model 57a). The insignificant coefficients of these contextual variables suggest that the corresponding health insurance scheme in the community did not impact residents' financial risk caused by using healthcare on average.

The significantly positive contextual effect of PHI on the occurrence of zero OOP payment in the urban east is theoretically good for equity. Literally, it means a one unit increase in the PHI prevalence level led to a 15.46-time increase in the odds of the occurrence of zero OOP payment in the community on average. It is also interesting that only in the urban east the utilisation level is also, though insignificant, positively correlated with the occurrence of zero OOP payment, while the correlation is negative in other areas (Table 7.19: Model 57a – 60a). It appears that in the urban east, the most affluent areas in China, there is an association between the higher PHI prevalence level and the higher probability of free healthcare for all. However, whether this should be attributed to PHI needs further research, maybe beyond information that the CHNS dataset can provide.

Table 7.18 The contextual financial protection – the Heckman models										
Population	*Total*		*Urban east*		*Rural east*		*Urban inland*		*Rural inland*	
Model	*Model 51a*	*Model 51b*	*Model 52a*	*Model 52b*	*Model 53a*	*Model 53b*	*Model 54a*	*Model 54b*	*Model 55a*	*Model 55b*
Risk level	*>50%*	*>90%*	*>50%*	*>90%*	*>50%*	*>90%*	*>50%*	*>90%*	*>50%*	*>90%*
Fixed effect: coefficient (S.D.)										
PHI Level	0.18(0.23)	0.34(0.27)	-0.79(0.55)	-0.17(0.68)	0.41(0.34)	0.40(0.43)	-0.08(0.45)	0.19(0.65)	0.78(0.85)	1.26(0.97)
SHI Level	0.02(0.09)	0.10(0.14)	-0.09(0.39)	0.27(0.48)	-0.12(0.21)	-0.15(0.30)	0.02(0.19)	0.18(0.31)	0.01(0.17)	0.05(0.24)
Utilisation level	-1.13(0.21)***	-1.17(0.32)***	-1.47(0.75)	-0.94(0.89)	-0.60(0.62)	-1.06(0.80)	-0.88(0.48) ˡ	-1.47(0.74) ˡ	-1.32(0.30)***	-1.11(0.42)**

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471 (Urban east: n=9265; Rural east: n=17210; Urban inland: n=19400; Rural inland: n=34870).

Significance values: ˡp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.

Adjusted for demographic, socioeconomic and aggregate variables like those in Model 8; The outcomes of the first equation on healthcare utilisation are not presented.

Table 7.19 The contextual financial protection – the ZINB models										
Population	*Total*		*Urban east*		*Rural east*		*Urban inland*		*Rural inland*	
Model	*Model 56a*	*Model 56b*	*Model 57a*	*Model 57b*	*Model 58a*	*Model 58b*	*Model 59a*	*Model 59b*	*Model 60a*	*Model 60b*
Equation	*%Zero*	*Count*	*%Zero*	*Count*	*%Zero*	*Count*	*%Zero*	*Count*	*%Zero*	*Count*
Fixed effect: coefficient (S.D.)										
PHI Level	0.55(0.41)	0.51(0.65)	2.74(0.97)**	0.89(1.24)	0.14(0.69)	0.08(0.86)	0.21(0.77)	-0.26(1.38)	1.02(2.03)	2.04(2.27)
SHI Level	-0.21(0.17)	0.17(0.27)	-0.18(0.45)	0.32(0.76)	-0.03(0.32)	-0.37(0.53)	-0.18(0.40)	0.76(0.51)	-0.25(0.34)	-0.04(0.38)
Utilisation level	-1.83(0.43)***	-0.77(0.57)	1.10(1.44)	0.13(1.37)	-1.61(1.12)	-1.37(1.20)	-1.81(0.87)*	0.17(0.96)	-3.07(0.73)***	-0.94(0.72)
Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,471 (Urban east: n=9265; Rural east: n=17210; Urban inland: n=19400; Rural inland: n=34870). Significance values: ˡp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001; Adjusted for demographic, socioeconomic and aggregate variables like those in Model 17.										

7.8 Impacts on living standards

Although this chapter focuses on the change of OOP payments for healthcare, the widely-used indicator of financial protection, it does not reflect the impacts on living standards, other element of the concept of financial protection (WHO, 2018). To complement the insufficiency, at the end this study adds an additional analysis of the relationship between health insurance and living standards, indicated by individuals' average grams of daily protein intake in past three days (for the reasons see Section 3.5.3). This study assumes that, in China, on average, the more grams of protein the individual consumes daily, the higher living standard he/she enjoys.

Table 7.20 descriptively explores daily protein intake among different insurance status. Based on the CHNS data, between 2000 and 2011, in China the average daily protein that an adult consumed was 66.01 grams, lower than the world average in 2001 – 75.8 grams (Zhu et al., 2005). Relating to health insurance status, there is a general pattern that those covered by SHI or/and PHI consumed more protein daily than those uncovered by SHI or PHI. This suggests that SHI and PHI enrolees appeared to enjoy higher living standards than the non-enrolees.

Table 7.20 Summary of daily protein intake by insurance status

	No PHI	*PHI*	*Total*
No SHI	64.39(38.17)	68.66(34.57)	64.52(39.44)
FMS	69.18(32.04)	70.38(32.01)	69.46(30.21)
Urban SHI	68.50(29.44)	73.61(29.32)	68.82(29.55)
NCMS	65.37(29.87)	72.02(29.70)	65.63(30.27)
Total	65.74(35.92)	71.08(33.79)	66.01(36.28)

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 81,755.
FMS = government employees' scheme; NCMS = rural SHI schemes.
Unit: gram
F tests show that difference in average gram of protein intake between SHI status and that between PHI status are both significant (p<0.001).

Fitting three-level linear models on daily protein intake (Table7.21)[41], demographically, being male and younger were significantly associated with higher daily protein intake. The negative effects of time passing are possibly attributable to age-related factors because participants get older year after year in longitudinal data. Health-related variables are significantly correlated with lower daily protein intake overall, but most these correlations are not significant abased on disaggregated populations. Importantly, there is a clear pattern that individuals with higher household income, lower household sizes, middle-level schooling (comparing to none or primary schooling) and working, were significantly associated with higher daily protein intake. At the aggregate level, local population density and economic activity were generally significantly associated with higher daily protein intake, especially in the poorest rural inland areas. Taken together, this demonstrates that other things being equal, in China protein intake was indeed associated with socioeconomic status and hence living standards likely.

After adjusting these demographic, socioeconomic and aggregate variables, based on the whole population, there is a marginally significant positive correlation between PHI enrolment and daily protein intake (Table 7.21). In addition, coverage of all SHI scheme has a significant positive correlation with daily protein intake. In terms of magnitude, being enrolees of PHI consumed 1.05 (95% CI -0.13 – 2.24) grams of protein more than those without PHI; being enrolees of FMS, urban SHI and NCMS consumed 1.29 (95% CI 0.27 – 2.32), 2.87 (95% CI 2.07 – 3.67) and 3.49 (95% CI 2.85 – 4.13) grams of protein more than those without SHI, respectively.

Furthermore, the disaggregation analysis shows that the positive correlations between health insurance schemes and daily protein intake were generally widespread across the country. It is noted that the correlation strengths of PHI with

[41] Unlike OOP payments, the individuals' daily protein intake data basically follow a normal distribution, and thus the OLS estimator is selected.

daily protein intake were lower than those of SHI schemes in most areas except the rural east, where the positive effect of PHI is significant (coef. = 2.36, 95% CI 0.55 – 4.17) while among SHI schemes only the positive effect of urban schemes is significant (coef. = 1.97, 95% CI 0.20 – 3.74). All together, these findings suggest that other thing being equal, health insurance coverage was associated with higher living standards. Comparatively, in most areas except the rural east, SHI schemes appeared to have stronger correlations with higher living standards than PHI.

Table 7.21 The three-level models on daily protein intake

	Total	*Urban east*	*Rural east*	*Urban inland*	*Rural inland*
Model	Model 61	Model 61a	Model 61b	Model 61c	Model 61d
Fixed effect: coefficient (S.D.)					
Year	Reference = 2000				
2004	-0.48(0.32)	-2.55(1.01)*	-1.25(0.68)ǂ	0.01(0.74)	0.09(0.44)
2006	-1.92(0.38)***	-2.79(1.17)*	3.08(0.78)***	-4.46(0.72)***	-2.92(0.54)***
2009	-3.53(0.46)***	-5.58(1.34)***	1.24(0.88)	-5.15(0.83)***	-4.91(0.71)***
2011	-5.29(0.46)	-7.38(1.27)***	-1.46(0.84)ǂ	-6.43(0.92)***	-6.44(0.77)***
Age	-0.21(0.01)***	-0.22(0.03)***	-0.21(0.03)***	-0.19(0.02)***	-0.21(0.01)***
Gender	9.76(0.23)***	10.41(0.77)***	11.23(0.50)***	9.22(0.46)***	9.17(0.31)***
Chronic diseases	-0.21(0.01)***	0.11(0.73)	-0.54(0.63)	-0.30(0.53)	-0.18(0.47)
Health status	-0.79(0.31)*	-0.70(0.84)	0.00(0.64)	-0.83(0.60)	-1.08(0.43)*
Household income	1.61(0.12)***	1.55(0.35)***	1.91(0.25)***	1.30(0.21)***	1.72(0.15)***
Household size	-0.69(0.09)***	-0.43(0.32)	-0.93(0.18)***	-0.73(0.17)***	-0.63(0.10)***
Education	Reference = no or primary school				
Middle or tech	0.88(0.24)***	2.00(0.88)*	-0.04(0.58)	1.64(0.62)**	0.87(0.36)*
University	0.22(0.58)	1.57(1.26)	-1.74(1.37)	1.36(0.89)	-0.54(1.40)
Working	2.69(0.28)***	2.35(0.86)**	3.23(0.56)***	2.29(0.51)***	2.81(0.36)***
Hukou	0.11(0.41)	0.96(1.39)	0.03(0.76)	-0.02(0.95)	0.24(0.60)
SHI	Reference = no SHI				
FMS	1.29(0.51)*	2.97(1.08)**	-1.50(1.25)	2.04(0.78)*	0.49(1.11)
Urban SHI	2.87(0.40)***	3.45(0.91)***	1.97(0.89)*	3.47(0.63)***	2.79(0.85)**
NCMS	3.49(0.32)***	5.83(1.29)***	1.05(0.66)	3.40(1.00)**	4.02(0.52)***
PHI	1.05(0.59)ǂ	-1.51(1.21)	2.36(0.91)*	0.44(0.87)	1.52(1.27)
Aggregate variables					
East	4.88(0.87)***				
Urban	-0.34(0.99)				

Health infrastructure	-0.01(0.06)	0.74(0.23)**	0.02(0.12)	-0.25(0.13)ᵻ	-0.08(0.07)
Transportation	-0.06(0.06)	-0.26(0.19)	0.02(0.13)	-0.26(0.15)ᵻ	0.04(0.07)
Economy	0.22(0.06)**	0.24(0.19)	0.16(0.13)	-0.09(0.12)	0.28(0.08)**
Social service	0.02(0.06)	-0.17(0.14)	-0.18(0.11)	-0.04(0.10)	0.41(0.09)***
Population density	1.42(0.23)***	2.35(0.51)***	2.26(0.50)	0.68(0.36)ᵻ	1.42(0.32)***
Random effect: variance (S.D.)					
Community-level	33.26(85.71)	31.74(85.96)	63.91(113.46)	18.60(69.74)	28.03(79.34)
Individual-level	37.65(55.96)	46.82(45.12)	35.87(50.72)	38.28(46.82)	35.93(45.80)
Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,745 (Urban east: n=9265; Rural east: n=17210; Urban inland: n=19400; Rural inland: n=34870). Significance values: ᵻp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.					

Conclusion

Due to the vulnerability of health expenditure data to violation of OLS's assumption of error distribution, this study applies the Heckman model to model the incidence of the OOP payments over the median (medium financial risk) and the incidence of the OOP payments over the 90^{th} percentile (high financial risk), respectively. The ZINB model is employed to model the OOP payments data as counts. Because a multilevel structure is not compatible with either the Heckman model or the ZINB model in the statistical package, this study uses the single-level structure with cluster-robust standard errors to handle the longitudinal data instead.

The findings show that the results of the two models are generally consistent. Based on the whole population, PHI enrolment neither had a significant correlation with a changed chance of financial risk for healthcare users, nor affected the amount of the OOP payments. It rather tended to correlate to a higher probability of positive OOP payments. After disaggregation, PHI also had no significant effects in all models based on the subpopulations.

By contrast, enrolment into all SHI schemes was significantly associated with a lower chance of medium financial risk and a higher probability of zero OOP payment. Except the urban SHI, enrolment of the NCMS and the FMS (marginally) was significantly associated with a lower chance of high financial risk. In the two east areas and the urban inland, all SHI schemes were associated with a lower chance of medium financial risk (with significance or marginal significance), but in the rural inland only the NCMS was. The NCMS were associated with a higher probability of zero OOP payment in the two rural areas (significantly for the rural east and marginally significantly for the rural inland), and with a lower amount of OOP payments in the rural east with marginal significance.

There is no evidence that dual insurance of PHI and SHI had an additional effect on financial protection. Among healthcare users SHI enrolees and PHI enrolees were associated with a higher chance of zero OOP payment compared to those without SHI and those without PHI, respectively, but unlike SHI schemes, PHI's such effect become mixed and insignificant after disaggregation. There were moderate changes in financial protection of SHI and PHI over time, but in most cases the changes were not significant. While most of the contextual effects of SHI and PHI are insignificant, in the urban east the PHI prevalence level in a community was associated with a higher average probability of zero OOP payment.

Finally, in terms of the impacts on living standards, indicated by individuals' daily protein intake, health insurance coverage was generally associated with higher living standards. Comparatively, in most areas except the rural east, SHI schemes appeared to have stronger correlations with higher living standards than PHI.

Chapter Eight: Discussion

This chapter summarises the findings from all three results chapters, individually and collectively, and discusses them in the context of existing knowledge and academic debate. Specifically, the first section summarises the key findings of this study and interprets them in the light of the literature review. The second section explores the contribution of this thesis to various academic debates, including issues about the inequalities that arise from private health insurance (PHI) and the appropriate role of PHI in efforts to achieve Universal Health Coverage (UHC). This is followed by a consideration of the methodological contributions the study provides in this area. The third section situates the analyses above in terms of national and global-level policy discussions. Finally, the chapter outlines the limitations of the study and makes suggestions for future research.

8.1 Summary and interpretations

In the first chapter of this thesis I raised the over-arching research question: what role has private health insurance played in meeting universal health coverage goals in China during the period of the scale up of social health insurance? By reference to the World Health Organisation (WHO)'s three-dimensional model of health coverage (WHO, 2008: 23-28), I subsequently break this question down into three groups of subsidiary questions, about the prevalence of PHI, its effect on access to healthcare and its financial protection. The study continues to follow this structure, presenting the results of the three corresponding results chapters (Chapters 5-7). This section sets out to summarise the key findings and carefully interpret them to show the extent to which these subsidiary research questions have been addressed, the extent to which the related research gaps identified by the literature review have been filled, and finally, what the general answer is to the over-arching research question.

8.1.1 The prevalence of PHI

There are four subsidiary questions about the prevalence of PHI, from descriptive to inferential. The interpretations focus on the unequal distribution of PHI and its relationship with SHI.

1) How has the prevalence of PHI changed over time?

This study shows that after a significant fall between 2000 and 2004, the prevalence of PHI, indicated by the proportion of PHI enrolees in the population, continuously grew from 2004 to 2011, but very slowly, especially in contrast to the rapid expansion of SHI (see Figure 5.1). Although this is just a simple descriptive analysis, few reviewed studies explored PHI prevalence over long time scales using individual-level survey data. Most related studies instead referred to the administrative statistics of total PHI premium income (China Insurance Regulatory Commission, 2014).

The prevalence fall between 2000 and 2004, rarely mentioned in the literature, coincided with a government policy issued in 2003 that abolished participating health insurance[42], which accounted for a considerable share of the PHI market at the time (Duan, 2008). Notably, the prevalence change does not accord with the monotonical increase of PHI premium income since 2000 in the administrative statistics (China Insurance Regulatory Commission, 2014). This difference may be caused by changing prices and population growth, so that PHI premium income cannot exactly indicate its prevalence. Only looking at the PHI income data would incur the risk of leading to an over-estimated conclusion about PHI prevalence. Additionally, PHI was mixed with life insurance in Chinese official statistics until the mid-2000s (Gu, 2009a,

[42] A combination of health insurance and investment that not only paid indemnity for critical illnesses but also regularly yielded dividends to attract consumers.

Duan, 2008), and there might therefore be inconsistent definitions for PHI between the two datasets at the early stage.

Notwithstanding the difference between 2000 and 2004, both sources of data show that PHI prevalence gradually grew since 2004. This process can be explained by overall economic growth, the increasing numbers of PHI suppliers and products (EY, 2016b), the dissemination of knowledge about PHI (Van de Ven, 2013: 51), and rapidly rising out-of-pocket (OOP) health expenditure (Figure 1.1), which led to the expectation of greater financial loss for using healthcare on average and thus resulted in a greater demand for PHI (Pauly, 2007: 28-31). However, the growth rate has disappointed advocates of PHI, not only for lagging far behind SHI in population coverage but also for still staying at a low level of the share in national health expenditure (Figure 1.2). Based on the debatable idea that PHI can help with insufficient SHI coverage, this is actually a standpoint calling for policy interventions for engaging PHI in China (Gu, 2009b, Xiang, 2014).

2) What are the individual and regional determinants of the prevalence of PHI and how have they impacted on the distribution of PHI?

This study identifies individual factors such as age, household income and size, personal education level, working status, *hukou*[43] and SHI membership, which were significantly associated with enrolment in PHI. In addition, the geographical location (east/inland), the type of community (urban/rural) and the development level of community health infrastructure were the aggregate factors that were significantly associated with enrolment in PHI.

It is worth noting that the findings based on the regression models are associational rather than causal. However, this does not mean it is impossible to discuss the

[43] A household registration institution in China, which divides the population into urban residents and rural residents based greatly on their/their parents' birthplace rather than their actual residence, not easy to move.

causality here. First and importantly, these identified factors are theoretically determinants of PHI enrolment, because they mostly belong to the theoretical model of healthcare utilisation determinants (Andersen and Newman, 1973, Andersen and Newman, 2005), and utilisation and the financial loss related to utilisation are key to the demand for PHI (Nyman, 2006). Second, these factors, as characteristics of individuals and their residence, exist before PHI enrolment. Third, these variables that correlate with both these characteristics and the purchase of PHI, such as the economic status and health status, as the theories show (Einav and Finkelstein, 2018, Sekhri and Savedoff, 2006, Arrow, 1963, Cutler and Reber, 1998), are taken into account in the models. Taken together, they are plausibly the determinants of PHI prevalence.

The findings show that PHI enrolment was significantly associated with individuals of higher socioeconomic status, represented by a greater household income, smaller household size, and who are educated and registered with urban *hukou*. At the aggregate level, the distribution of PHI was also associated with more affluent communities, i.e. those in the east of China, in urban areas, and with higher levels of health infrastructure, particularly strengthening the evidence for the spatially unequal distribution of PHI in favour of more affluent areas, for which the literature review gives weak evidence.

According to the findings, more affluent eastern and urban areas exhibited higher PHI prevalence, compared to poorer inland and rural areas, even controlling for individual factors. This suggests that, in addition to those residents' characteristics that potentially lower the prevalence of PHI in the poorer areas, these areas themselves possess some features that negatively influence PHI prevalence. There may be, for example, fewer PHI selling agencies, lower popularisation of PHI information, and poorer cooperation between insurers and healthcare providers. Consequently, the unequal distribution of PHI in China has been multilevel, in favour not only of more affluent people but also more affluent areas. Conversely, poorer people living in poorer areas would be the least covered by PHI.

The associations between PHI enrolment and traditional socioeconomic factors such as income and education suggest that the distribution of PHI in China shares a similar pattern to the rest of the world, where socioeconomic factors are strong determinants of PHI purchase (Colombo, 2007: 223). What is more, the China-specific *hukou* system, where urban *hukou* is associated with privilege in other crucial respects (Liu, 2005), also contributes to this inequality. Theoretically, socioeconomic characteristics facilitate utilisation as the enabling factors, according to the classic health utilisation model (Andersen and Newman, 2005). The positive relationships between PHI enrolment and higher socioeconomic status may have in effect strengthened the substance of the enabling factors in determining utilisation. This is inconsistent with the equity of access principle, which emphasises needs-based utilisation instead (O'Donnell and Wagstaff, 2008: 1).

3) Have the effects of these determinants varied across China and in what patterns?

This study further finds that some identified determinants of PHI enrolment have uneven effects across the four areas types in China, i.e. the urban east, the rural east, the urban inland and the rural inland, which few studies in the literature have explored. The positive effects of household income and education level, the two typical indicators of socioeconomic status, were relatively strong in substance in the poorest rural inland area compared to others, suggesting the unequal distribution of PHI between people of different socioeconomic status was greater in poor areas.

Additionally, community population density was significantly associated with increased prevalence of PHI in rural inland areas but with reduced one or had insignificant effects in other wealthier regions. This possibly suggests the relatively prudent marketing strategies of commercial insurers in the poor areas, where consumption is lower, residential communities are often remote and settlements are widely scattered. Therefore, insurers may tend to concentrate on more populous communities to market their products in order to reduce costs. There is a little evidence that Insurers' risk aversion against poor areas in China in the literature (Liu and Wang, 2012, Qu and Wang, 2010), and deserves more attention in the future. Besides this, the health infrastructure level of the community was significantly or marginally significantly associated with increased PHI enrolment in all but rural inland areas. It may relate overall to such a poor quality of health infrastructure in these areas, that a slight change did not substantially impact utilisations and costs, and thus had little influence on PHI prevalence.

In addition to the individual and aggregate determinants, the model unobserved variation in PHI prevalence (i.e. residuals not explained by the model variables but captured as random effects) was greater in rural areas than urban areas. Regarding rural areas, the variation is attributed more to the community difference in the more affluent rural east, but more to the individual difference in the poorer rural inland. Together with the above findings, PHI distribution appeared in general more equal across individuals and communities in more affluent areas, while in the poorer area, it appeared more inclined to be determined by unsystematic, individual factors.

4) What are the relationships between enrolment under an SHI scheme and PHI enrolment, and how have these relationships changed with the growth of SHI?

This study finds that those with SHI were more associated with enrolment into PHI than those without SHI in 2000. However, this correlation fundamentally changed; from 2004 to 2011, those with SHI in general became less associated with enrolment into PHI than those without SHI. This pattern was prevalent, found not only among the whole study population, but also among all four subpopulations after disaggregation, and between all SHI schemes and PHI. This finding may help to address an important gap in the literature, which gives mixed evidence about the impact of SHI coverage (and expansion) on PHI enrolment.

To interpret this result, first of all, as SHI increased its coverage from a small proportion to most of the population, the socioeconomic difference between SHI enrolees and non-enrolees diminished. As this study also demonstrates, in the early 2000s, relative to SHI enrolees, non-enrolees of SHI were on average poor, with a low level of education, living in rural and inland areas and with rural *hukou* registrations, which were also typical of PHI non-enrolees relative to PHI enrolees. However, at the end of this period, these distinctions became obscure, except for *hukou* where SHI enrolees were even more likely to be registered in rural areas than SHI non-enrolees. As a result, SHI enrolees' likelihood of PHI enrolment compared to that of SHI non-enrolees was bound to reduce, as the former's socioeconomic advantages over the latter reduced.

Second, it is worth discussing the impact of SHI coverage itself on PHI enrolment, although the findings are not causal due to the limitations of the study design. Because enrolment into SHI in China, including those so-called "voluntary" schemes like NCMS, is strongly driven by political targets rather than individuals' demand (Liang and Langenbrunner, 2013), its enrolment is not likely to be affected by PHI. In addition, the common individual and aggregate characteristics, as the potential causally prior variables, have been controlled for in the models to some degree. Thus, the association between SHI and PHI possibly suggests that SHI coverage impact enrolment in PHI, rather the other way around.

From this point of view, the change in the relationship between SHI and PHI may relate to the increasing benefit coverage of SHI. SHI enrolees' falling association with PHI enrolment against those without SHI happened along with the former's access to an increase in the benefits offered by SHI (Liang and Langenbrunner, 2013, Yip et al., 2012, Meng et al., 2012), which the latter did not enjoy at all. This suggests that there may be a negative relationship between the benefits individuals receive from SHI and their likelihood of PHI enrolment. It is in line with the theory that as SHI benefits become more and more widespread and generous, room for the PHI market diminishes as many of its benefits are available more cheaply via SHI (Barros and Siciliani, 2012). This will be discussed in detail later (Section 8.2.2).

However, in 2000, when health financing had been long dominated by OOP payments in China, the introduction of SHI might have increased the take-up of PHI through a number of theoretically-possible mechanisms, including SHI-driven popularisation of knowledge about health insurance (Van de Ven, 2013: 50-52), increases in household disposable income, from which funds to buy PHI could be sourced (Liu et al., 2011b), the increased incentive for commercial insurers to attract consumers from across different socioeconomic groups as SHI ate into their market share (Barros and Siciliani, 2012), and increased governmental capacity to establish regulations that enhanced and stabilised the health insurance market (Zweifel and Pauly, 2007: 117-121). What is more, at that time, SHI benefit coverage in China was too limited to encroach much on PHI's niche.

It is worth noting that the literature review gives strong evidence that at the macro level SHI expansion is positively associated with the rise of total PHI premium income (Li, 2009, Wang, 2009, Wang, 2011, Zhu and Gui, 2014, Wang et al., 2015, Zheng and Hua, 2013, Lv, 2013). It appears to disagree with the finding based on the individual-level data. However, as I argue in the literature review, PHI income is not only correlated with prevalence, but also determined by other factors such as the price of PHI, population structure, economy and so on (Li, 2009, Wang et al., 2015). Thus, examining only the macro income data might lead to a one-sided conclusion about the relationship between SHI and PHI.

8.1.2 The effects on access to healthcare

There are four subsidiary research questions under this topic. They begin with the effect of PHI on its enrolees' access to healthcare and complement to SHI. They then extend to interrogate the spatial inequality in the effect and the contextual effect on residential communities.

5) How has PHI impacted on access to healthcare among its enrolees?

Access to healthcare is mainly indicated by utilisation. The literature review finds mixed evidence for the impact of PHI on the generic utilisation of healthcare (a combination of outpatient and inpatient care) and little evidence for its impact on outpatient healthcare. This study found little difference in the association with generic utilisation between PHI enrolees and those without PHI in the general population. Narrowing the population to the high-need group (those who were self-reportedly ill or injured at that time), PHI enrolees' association with utilisation substantially increased against those without PHI and reach significance. On the contrary, SHI enrolment was significantly associated with higher utilisation in the general population, but this association significantly reduced within the high-need group.

It is noteworthy that, based on the research methods, the findings about the relationships between insurance and utilisation are *associational* rather than *causal*. However, there are reasons for discussing causality. First, in theory, coverage of health insurance is an enabling factor in the classic utilisation determinants model (Andersen and Newman, 1973, Andersen and Newman, 2005), facilitating healthcare utilisation by reducing financial barriers (Arrow, 1963, Pauly, 1968, De Meza, 1983, Nyman, 2006). Second, in terms of the CHNS measurement, utilisation is whether the event occurred in past four weeks, while enrolment in insurance is contemporary status, entrance into which was possible but not likely to happen within recent weeks. Thus, joining health insurance programmes generally happened prior to using healthcare. Third, while enrolment in SHI is compulsory or semi-compulsory (Liang and Langenbrunner, 2013), the potential causally prior variables for PHI enrolment and utilisation are specified according to the theory (Andersen and Newman, 1973, Andersen and Newman, 2005) and controlled for in the analytical models, to some degree. To sum up, it is reasonable to cautiously discuss the impacts of SHI and PHI on healthcare utilisation.

To interpret the results from the perspective of the theory that health insurance affects utilisation by making healthcare more financially affordable (Musgrove, 2007: 171-172), it is necessary to relate to the compensation policies of SHI and PHI. As previously mentioned, in China SHI focuses on basic coverage (Yip et al., 2012), commonly offering payment of the fees for seeing doctors, basic health services and generic drugs, with deductibles and co-payment varying across schemes and regions (Liang and Langenbrunner, 2013). By contrast, PHI policies increasingly concentrate on complementing or supplementing SHI (Xiang, 2014), thanks to government guidance and the strategies of commercial insurers in coping with SHI expansion. Thus, PHI policies usually include partly compensating treatment for a few major diseases (Liu et al., 2011b), filling the uncovered part of SHI, especially for extended inpatient care (EY, 2016b), or even giving a one-off payment if a critical illness is diagnosed (Ng et al., 2012).

In the general population, among whom most are healthy and hence the average expectations of needed healthcare and financial loss are low, compensation from SHI, rather than PHI, is more likely to happen. As a result, on average only SHI significantly reduced the expected loss and hence increased utilisation. However, when shifting to the high-need group, who, driven by need, were already very likely to use healthcare regardless of health insurance, the influence of SHI on utilisation was comparatively reduced, due to its limited benefits. Instead, PHI began to come into play because the high-need group's average expectation of needed healthcare and financial loss were substantially higher than that in the general population; high enough to expect compensation from PHI so as to reduce the expected financial loss.

6) How has PHI 'complemented' SHI in terms of providing additional access to healthcare for covered individuals?

When taking the dual insurance of SHI and PHI into account, PHI was found to be associated with utilisation in the high-need group only when SHI was present. The possible explanation is that the combination of SHI and PHI was effective to substantially reduce the expected (not real) OOP spending on healthcare, and hence increased utilisation. Before taking dual insurance into account, the significant association with utilisation of PHI occurs because a considerable proportion of PHI enrolees also had SHI. This suggests that SHI plays a very fundamental role in facilitating utilisation, though it appears not to help those in high need sufficiently, while PHI can complement SHI for their enrolees in the high-need group.

This finding should contribute to fill the gap in the literature. According to the literature review, most previous studies did not particularly discuss the combination of SHI and PHI, possibly because their data involving dual insurance cases were scarce (Qin et al., 2014, Chai, 2014, Chau, 2010, Zang et al., 2012). Two studies looking at the combination did not find any significant advantage of dual insurance over any kind of single insurance regarding utilisation, but did not give an explanation for their results (Lam and Johnston, 2012, Chai, 2013, Yang, 2013). Their inconsistencies with the findings of this study may be attributed to sampling differences. Both studies used cross-sectional data and only examined one city or two provinces. In contrast, this study uses multi-provincial, longitudinal data, with a much larger sample size.

7) How do the effects of PHI on healthcare access vary across regions?

This study finds that the association of PHI with the utilisation of healthcare varied spatially. First, for the high-need group, PHI's association with utilisation was less in rural inland areas than in other wealthier areas. Second, cross-community variation in the effect of PHI on utilisation was eight to ten times as high in the rural inland as it was in urban areas, and close to four times as high as it was in the rural east. This suggests that the performance of PHI on utilisation in poorer areas was more unequal across communities than it was in more affluent areas.

In fact, SHI also showed unequal associations with utilisation, not only among schemes but also among areas. For example, the government's Free Medical

Scheme (FMS) was significantly associated with utilisation in all but the rural inland; the New Cooperative Medical Scheme (NCMS), only had such association in rural areas though it also covered considerable urban residents (most registered with rural *hukou*); the urban SHI (combination of employees' and residents') had little such association at all. Shifting from the whole to the high-need group, and compared with those without SHI, the utilisation-association of SHI reduced more in rural areas than in urban areas, suggesting poorer realisation of SHI benefits in rural areas.

The literature review gives weak evidence by one study based on the 2008 two-province data that PHI is more likely to increase utilisation in urban areas than in rural areas. The present study not only gives supporting evidence based on broader and longitudinal data, but also adds that PHI's such effect is even more variant in rural areas than in urban areas. Taken the results of SHI above together, this study shows that in terms of spatially unequal performance on utilisation, PHI has not complemented the inequality that SHI made and might have rather increased it.

To explore the reasons for the inequality, for SHI it is plausibly attributed to the fragmentation in pooling, funding, and administration (Meng et al., 2015). However, for PHI, whose products are mainly managed by large national or international insurers (Gu, 2009b), this phenomenon may be attributed more to China's unequal distribution of healthcare resources instead (Yip and Hsiao, 2014), because PHI relies heavily on the cooperation of local healthcare supplies (Colombo, 2007: 229-230). In China, that eastern, urban areas are significantly more developed and wealthier than inland, rural areas is a long-lasting source of inequality (Liu, 2005, Liu et al., 2003, Shi et al., 2010). Specifically, in urban areas, healthcare supplies tend to be abundant and well-distributed, whereas in rural areas, especially the remote, less-advanced rural inland, supplies are often limited and scattered (Blumenthal and Hsiao, 2005). As a result, unequal availability of health resources and access to them contribute to PHI's unequal associations with utilisation across these areas. Besides this, in rural areas, the locations of residential communities are less concentrated and therefore the residents of different communities have more varying distances to travel to health facilities than those in urban areas, also contributing to the larger cross-community variations in PHI's effect on utilisation in rural areas. These above of course contribute to SHI's such unequal associations with utilisation as well.

8) What is the impact of PHI on average access to healthcare in each local context?

This study finds a pattern that, in the east, the PHI prevalence level in the community was increasingly associated with higher average utilisation as the average need level increased. On the contrary, inland, under the same conditions, the prevalence of both SHI and PHI in the community was increasingly associated with lower average utilisation, especially in rural areas. The literature review does not find any previous study that examine PHI in China from this perspective.

The common explanation for the negative contextual effect is that health insurance distorts the allocation of resources in favour of membership rather than needs (Kutzin, 2013). When health resources are limited, which is more likely to happen in poorer areas, health insurance reallocates resources to let its enrolees enjoy more healthcare, but in effect this deprives others of access to it. This makes the health system more ineffective, because it is not to meet needs, which consequently reduces average utilisation in the whole community (Colombo, 2007: 229-230). For the concept of UHC, this is in conflict with the equity principle (Kutzin, 2013), but was observed in many health systems (Colombo, 2007: 223-224, Kutzin et al., 2016). On the contrary, the positive contextual effect in the east indicates that the health insurance programme benefits the whole community's utilisation, therefore contributing to health equity. For SHI, as its coverage becomes universal, the importance of the contextual impact relatively reduces. However, for PHI, since it only coverages a small number of people, likely the more affluent, inequity of access from its contextual impact deserves attention.

8.1.3 Financial protection

There are also four subsidiary questions about the financial protection provided by PHI. The first two questions are concerned with the financial protection of PHI enrolees and its financial complement to SHI. The remaining two shift attention to inequities that PHI has caused.

9) Has PHI reduced the financial risk incurred by using healthcare for its enrolees?

This study finds that PHI enrolment was not significantly associated with the financial risk caused by using healthcare in China, no matter which indicators of the financial risk were used. This is consistent with the result of the literature review but based on more reliable methods. A plausible explanation is that PHI caused higher gross health expenditure – not measured in this study but sufficiently attested to in the literature (Wang et al., 2010, Chen et al., 2009, Yuan et al., 2014, Fang et al., 2012, Chai, 2013) – because PHI increased the utilisation of healthcare for those in need (as this study suggests) and also possibly allowed its members to use a larger amount of unnecessary services due to moral hazard in some cases (Musgrove, 2007: 171-172, Pauly, 1968). Meanwhile, most PHI policies still consist of deductibles, co-payments and a compensation cap like SHI (Blomqvist, 2009), also resulting in OOP payments. Taken together, PHI may push up gross health expenditure on the one hand, and partially reimburse it on the other, consequently leading to an overall insignificant change in OOP payments.

By contrast, SHI demonstrated the negative association with the occurrence of financial risk. In terms of significance of the associations, it suggests that SHI schemes were more effective at reducing medium financial risk (defined as the OOP payment for healthcare exceeding the median of the sample OOP payments in this study) than high financial risk (the OOP payment for healthcare exceeding the 90th percentile of the sample OOP payments). In addition, SHI schemes were associated with the occurrence of zero OOP payment for healthcare, and these effects occurred particularly along with utilisation of healthcare, but had little direct impact on the amount of OOP payments, suggesting that SHI schemes may have offered enrolees free healthcare, probably very basic services or medicines, but could not effectively control OOP payments once they had happened. In one word, SHI may reduce OOP payments, which was restricted to a low level, however.

The additional analysis finds that PHI coverage was marginally significantly associated with higher daily protein intake, and all SHI schemes were significantly associated with higher daily protein intake. Because the acknowledged relationship between daily protein intake and living standards, especially in Asian developing countries (Zhu et al., 2005, Zhen et al., 2010), this suggests that coverage of health insurance may have a positive impact on living standards, other things being equal. This correlation was reported previously in China (Xie and Han, 2015, Wu et al., 2016).

The possible explanation is that although coverage of health insurance in effect had a limited effect on OOP payments for healthcare as this study found, it indeed reduced insurance enrolees' expectation of OOP payments and hence increased their expenses on everyday living including consumption of better food (more protein intake). On top of these, because of the limitation of the study design, selection of enrolees of health insurance, especially PHI as this study shows (PHI enrolees have relatively high socioeconomical status), might contribute to the relationships. Taken together, coverage of health insurance possibly helped to improve living standards, where the performance of PHI was also inferior to SHI.

10) How has PHI complemented SHI in terms of financial protection for covered individuals?

Given the finding that PHI has not been associated with reduction of OOP payments, PHI has not complemented SHI in financial protection for covered individuals. Furthermore, this study does not find that dual insurance additionally influences the financial risk, no matter whether the examination focused on the general population or just healthcare users. In addition, adding their interaction had little impact on the effects of the SHI and PHI in the model, which implies that the compensation procedures of SHI and PHI may be so separate from each other, that they barely impacted each other's performance. For a better complementary role of PHI as the government expects (Xiang, 2014), more effort would be needed to promote the public-private cooperation in financial protection. Notwithstanding the neutral result, the finding may contribute to the literature with new evidence as the literature review finds no study explored this before.

11) Has PHI provided spatially unequal financial protection?

This study finds no significant association of PHI with OOP payments based on the whole population or subpopulations after disaggregation, and it is also hard to find any meaningful pattern across different areas of China. This is possibly because of, first, the spatially-varied effects of PHI on the utilisation of healthcare, and second, the different prices of healthcare across these areas (Yip and Hsiao, 2009a), consequently resulting in mixed, insignificant PHI financial protection across these areas.

Comparatively, SHI shows a pattern where its schemes' financial protection was likely to be relatively weak in the poorest rural inland areas. Concretely, compared to the other three regions, where all SHI schemes were significantly negatively associated with the occurrence of medium financial risk, only the NCMS was in the rural inland. The FMS was significantly associated with the occurrence of zero OOP payments in all but the rural inland. The NCMS was significantly associated with the occurrence of zero OOP payment in all rural areas. It was also marginally significantly associated with the reduced amount of OOP payments once they happened in the rural east, but it was not in the rural inland.

In terms of the impact on living standards for subpopulations, the association between PHI and daily protein intake was only significant and positive in the rural east areas, and the associations between SHI schemes and daily protein intake were relatively weak in the areas. It is possibly because compared to other areas in China, people in the rural east have higher expectation of PHI compensation, but lower expectation of SHI compensation, implying greater market potential of PHI in the rural east.

12) What is the impact of PHI on the average level of financial risk in a local context?

Like its effect on the enrolees, the associations of PHI with the community's average financial risk were also insignificant in most areas. The only exception is the urban east, where the PHI prevalence level in the community was significantly associated with the occurrence of zero OOP health payment to a community member and thus appeared to have contributed to the equity ideal of UHC. However, it does not seem convincing enough to attribute this to PHI itself, since the prevalent cost-sharing policies of PHI inevitably cause OOP payments (Blomqvist, 2009). It may be related to a combination of lower utilisation and higher PHI prevalence in the urban east, compared to other areas, as this study found (Table 5.6 and Table 6.6). In addition, possibly, in the most affluent areas, there is an association between the higher PHI prevalence level and the higher probability of free healthcare, related to some unknown aggregate-level characteristics; this needs further research.

Despite the unclear mechanisms, this finding provides a new insight into financial inequities of PHI in China. Echoing this finding, one provincial-level study reported that the PHI development level[44] was significantly associated with lower per-capita health expenditure in eastern China (but with higher such expenditure in inland China), but did not give a clear explanation for this (Suo et al., 2015). In the literature review, most related studies focused on the vertical equity of PHI to evaluate its financing distribution across income quintiles, reporting very mixed results. However, due to the limited pooling level of PHI in China, unlike SHI, the vertical equity for PHI is in effect not very telling.

[44] Indicated by an index created by the authors that considers PHI premium income, GDP, population and the number of insurers.

8.1.4 The synthesis of key findings

The findings of the analyses have given answers to all of the subsidiary research questions and helped to address these research gaps identified by the literature review in Chapter 2. These answers are combined here to give a fuller account of the role that PHI plays in China's progress to UHC.

In China, to its enrolees – a small proportion of the population – PHI was likely to offer potential for increased access to healthcare when needed and increased living standards, without raising the related financial risk (OOP payments for healthcare). However, PHI was unequally distributed, with enrolment higher among individuals of higher socioeconomic status and, at the aggregate level, in the more affluent eastern and urban areas than in the poorer inland and rural areas. Its utilisation-promotion effect also tended to be stronger and more homogeneous among communities in these wealthier areas. In addition, it benefited whole communities in the more developed east but have an opposite effect in the less-developed inland areas. From 2004 to 2011, PHI prevalence grew very slowly, comparing with the booming SHI, and individuals with coverage under SHI became less likely to have PHI than those without SHI.

In short, PHI contributes slightly to health coverage by benefiting a minority of the population, but systematically causes socioeconomic and spatial inequalities in insurance coverage and access to healthcare. As SHI expands, its importance as a source of coverage in effect reduces.

8.2 Associations with theory and recent developments

After relating the findings to the research questions, this section sets out to interpret the findings under the established theoretical frame (for details see Section 1.3).

Additionally, it extends the interpretation by connecting them with the recent developments in PHI and SHI after 2011.

8.2.1 Association with the theoretical frame

In terms of prevalence of PHI, high OOP payments for healthcare[45] and individuals' risk-aversion theoretically underlie the demand for PHI (Pauly et al., 2009), but the market forces, the market failures as well as poor regulations in the developing countries impede its coverage expansion (Arrow, 1963, Van de Ven, 2013: 51, Cutler and Reber, 1998, Zweifel and Pauly, 2007: 117). This study suggests that although healthcare-related financial risk has been high for many people in China for some time (Meng et al., 2012), a factor that should support demand for PHI, institutional impediments may dominate the market, resulting in very slow growth and unequal distribution of PHI prevalence. In addition, as SHI expands, OOP payments for healthcare reduce (or perceptually reduce among SHI enrolees), undermining the demand for PHI.

Regarding access, health insurance theoretically confers greater access to healthcare mainly by lowering the costs of utilisation (Andersen and Newman, 1973, Aday and Andersen, 1974, Van de Ven, 2013: 51-52). Although selection of enrolees may confound the correlation between insurance coverage and healthcare utilisation, the findings of this study accords with the theory, plausibly suggesting that the individual characteristics that determine insurance enrolment have been fairly controlled for in the models. Furthermore, the insurance-related additional utilisation is theoretically more efficient when it happens to satisfy unmet needs for those who are ill (Nyman, 2006). Otherwise, it could be sub-optimal consumption due to the moral hazard (Pauly, 1968, Einav and Finkelstein, 2018). The findings of this study suggest that the additional utilisation associated with PHI may be less likely to be attributable to the

[45] This is determined by coverage of SHI. Further discussion about the impact from SHI is presented later.

moral hazard than that associated with SHI schemes, because the former is more responsive to high-need status (being ill or injured) than the latter.

The degree of financial protection provided by health insurance, principally in terms of reduction in OOP payments for healthcare, can be difficult to assess due to the fact that reduced financial barriers to access afforded by insurance are likely to push up demand and thereby prices, some of which will be borne by consumers in the form of higher co-payments or deductibles (Pauly, 1968, De Meza, 1983), but do not comprehensively compensate costs of healthcare on the other (WHO, 2010b), especially in developing countries (Pauly et al., 2009). In fact, it may be access to healthcare rather than financial protection that is playing a central role in the demand for health insurance (Nyman, 2006). Thus, it is not theoretically surprising that this study does not find a significant association between PHI enrolment on OOP payments. Regarding the impact on living standards, the other aspect of the concept of financial protection, the positive relationship between coverage of health insurance including PHI and living standards possibly reflects the feelings of financial security among enrolees, so that they spend more in improving quality of life, although in reality the feelings may not be true considering OOP payments.

8.2.2 Interpretation under recent developments

Due to the limitation of data availability and time schedule, the analytical part of this study examines data collected between 2000 and 2011. But in the final discussion it is worth surveying the findings with the recent developments in China. Since 2011 the economy continues to grow fast, guaranteeing sustainable money injected into the employment-based UEBMI and the tax-funded FMS and steadily increasing subsidisation of the residence-based NCMS and URBMI (Liang and Langenbrunner, 2013). For example, from 2013 to 2016, the per-capita contribution to the UEBMI revenue increased by 35.2% from ¥2573 to ¥3479; the per-capita individual contribution to the NCMS revenue increased by 50.7% from ¥371 to ¥559 (National Health Commission, 2018).

While the SHI coverage breadth has been fairly high in 2011 (Meng et al., 2012), the government continues to strengthen the coverage depth by adding more drugs and services into the list of SHI reimbursement items and the coverage height by increasing the reimbursement ratios and caps (Liu et al., 2017, Meng and Xu, 2014). As a result, the share of insurance expenditure (predominantly SHI) in total health expenditure rose from 30.7% in 2011 to 42.3% in 2017 (National Health Commission, 2018). Relating to the findings of this study, as SHI was associated with greater utilisation of healthcare and moderate financial protection, the recent efforts would reinforce the efficacy of SHI.

However, from other viewpoint, the recent developments in SHI suggests that the additional utilisation and financial protection associated with SHI coverage found by this study was not considered enough by policy makers. In fact, from 2011 to 2017, although the share of OOP payments in total health expenditure reduced from 34.8% to 28.8% (National Health Commission, 2018), it is still higher than the maximum rate of 15-20% above which financial catastrophe is unlikely to be effectively prevented according to the WHO (2010a). Additionally, the reduction rate slows down in last three years to 2017: the share of OOP payments reduced by less than one percentage point, while the absolute value of OOP payments increased by 26.2% (National Health Commission, 2018), suggesting that the financial risk that result from high OOP payments is not going away anytime soon.

As the result of the persistently high OOP payments due to the insufficient coverage of SHI, the demand for PHI is likely to be sustainable. From 2011 to 2017 the PHI premium income grew from 69.2 billion yuan to 438.9 billion yuan (China Insurance Regulatory Commission, 2018). However, in terms of enrolment, neither the latest 2013 NHSS data nor the newly-published 2015 CHNS data show the percentage of

PHI enrolees in the whole population increasing compared to the last survey wave (National Health and Family Planning Commission, 2015a). Especially, regarding the CHNS data, the overall percentage of PHI enrolees reduces from 4.20% in 2011 to 2.67% in 2015. As the prevalence of PHI stagnates, the increase of total premium income may be attributable partly to the fast-increasing total health expenditure, which more than doubled from 2011 to 2017 (National Health Commission, 2018), consequently increasing the average price of premium. The inconsistency in growth between PHI prevalence and total premium income also implies that China's PHI market is moving upmarket, raising prices but narrowing the range of customers. This trend derives from the target of complementing SHI for UHC.

These updates primarily show once more the difference between the macro-level income data and the micro-level enrolment data of PHI, and the merit of the studies on the latter, considering that most related studies focused on the former. This also attests the finding of this study which suggests that PHI prevalence would not substantially increase partly attributable to the negative impacts of SHI memberships on enrolment into PHI as SHI expands. Since 2016 the individual-income-tax (IIT) break policy for promoting PHI has been gradually introduced. Its impacts on PHI prevalence is subject to examination and its rationality will be discussed in more details in the later policy implication section. Except income or enrolment data, in these common statistics or surveys there still lacks more informative data about PHI, especially about its benefit coverage after 2011, preventing deeper understanding about PHI.

8.3 Academic contributions

This section highlights the potential contributions of this study to the corpus of academic knowledge. Above all, it is the first comprehensive investigation of PHI from the perspective of UHC objectives in China that is based on empirical data rather than theoretical analysis. It offers an interrogation of PHI's impact on equity and establishes a reconsideration of PHI's role in the UHC project. Additionally, it gives methodological advice for those who are going to use the China Health and Nutrition Survey (CHNS) dataset, one of the most popular longitudinal household survey datasets about health in China.

8.3.1 Extending knowledge about inequalities that arise from PHI

PHI has long been criticised for being a source of inequity (Kutzin et al., 2016, Colombo, 2007: 223, 232). Unlike typically progressive SHI with compulsory (or semi-compulsory) enrolment and income-related contributions, PHI enrolment is voluntary and contributions are risk-related (Sekhri and Savedoff, 2006), unless it is heavily regulated (Enthoven and van de Ven, 2007). The ability to pay is the precondition for the purchase of PHI (Van de Ven, 2013: 51). Due to information asymmetry, adverse selection occurs as commercial insurers tend to set premiums higher to prevent unknown risk, and under *laissez-faire* policies, adverse selection can lead to such high prices that only affluent people can afford PHI (Sekhri and Savedoff, 2006). Furthermore, the risk selection of insurers causes premiums for older and unhealthier people to be even higher (Pauly et al., 2012).

In theory, therefore, PHI disproportionately enrols high-income earners, and PHI brokers cluster in areas where the affluent are concentrated (Zweifel et al., 2007: 94). Most international (Salti et al., 2010, Barros et al., 2011, Sekhri and Savedoff, 2005, Mills et al., 2012) and domestic studies (Liu and Wang, 2012, Zang et al., 2012, Dong and Zhao, 2013, Yue and Zou, 2014) gave the individual-level evidence for this. The current study goes further, showing that in China PHI is unequally distributed, tilting not only towards individuals with higher socioeconomic status (higher household income, smaller household size, better educated and registered with urban *hukou*), but also the more affluent areas like the eastern and urban areas, controlling for individual characteristics.

The multilevel unequal distribution of PHI has three implications. First, PHI increases inequality in access to healthcare: its enrolment is in part positively correlated with affluence, and therefore lets the more affluent potentially gain more health resources, given its potential utilisation-promotion effect. Second, inequality emerge not only on the demand side but also on the supply side: insurers are inclined to market PHI harder in more affluent areas, as described above (Zweifel et al., 2007: 94). Third, people living in poor areas therefore have lower access to PHI than those of similar affluence, and poorer people in poorer areas, who should be key targets of the UHC programme, are especially neglected by PHI.

Apart from unequal distribution, PHI causes other inequalities. This study shows that in China the effects of PHI can vary heavily among the regions: its association with utilisation was higher and more equally among communities in the more affluent areas, typically the urban east, than the poorer ones, typically the rural inland. In addition, PHI was relatively more associated with the benefits of the whole local community in the east, especially the urban east, which suggests that PHI appears even more equitable in more affluent areas than poorer areas in China. These differences may be attributable to the unequal abundances of local health resources, as discussed in the preceding section.

In contrast to PHI, SHI, whose enrolment was unequal and socioeconomically biased when it was initiated, nevertheless, became progressively more equal and even equitable. As this study shows, in 2011 the socioeconomic disparities between the enrolees and non-enrolees of SHI have almost been eliminated. In particular, the privileged urban *hukou*, once associated with a much higher rate of SHI enrolment, became associated with a lower rate of SHI enrolment than the rural *hukou* (see Section 5.4.4). Other than prevalence, this study nonetheless finds that inequality in

SHI benefits in utilisation and financial protection persists among SHI schemes and between the more affluent east, urban areas and the poorer inland, rural areas. Those who receive the poorer SHI benefits, such as those without SHI and urban NCMS enrolees, were more likely to have PHI since 2004 than other SHI enrolees (Section 5.4.3), suggesting that the SHI's among-scheme inequality may be reduced by the complement of PHI. Contrarily, the spatial inequality of SHI may be intensified by PHI's pro-wealth distribution.

In conclusion, in a large and unequal country like China, concerns about inequality issues should be indispensably extended from the individual-level factors such as income and education to the aggregate level, involving at least geo-economic factors. A key reason is that these aggregate differences are not completely reflected in individual differences. Instead, they may be embodied in insurers' marketing actions, which influence access to PHI selling in certain areas, as well as local health supplies that facilitate PHI application. Poor individuals are likely to cluster economically undeveloped regions, where PHI insurers neglect the market and the local health delivery system responds poorly to PHI. Consequently, the inequality problems caused by PHI in the whole system could be far more serious than estimations based on considering individual-level factors.

8.3.2 Rethinking the role of PHI in progress to UHC

UHC is central to all health reforms (WHO, 2013), but there is no single, optimal path for moving systems towards this target (WHO, 2010a). Evidence shows that countries which have approached UHC effectively rely almost completely on dominant public sectors with various mechanisms (Musgrove et al., 2002). However, for those still on the path – mostly developing countries – limited government revenue can be a critical impediment to UHC.

It is argued that PHI could relieve the fiscal burden of government as "a critical pillar of a robust health financing system" (Preker, 2007: 6), as it replaces the OOP payment, which is the cause of household financial risk (Sekhri and Savedoff, 2005). Notwithstanding this, the inherent features of PHI markets, such as voluntary enrolment, adverse selection, 'cream skimming', and moral hazard, fundamentally prevent PHI from universal coverage, especially under *laissez-faire* policies (Sekhri and Savedoff, 2006). As a result, public-private mix financing methods are often prescribed for developing countries (Scheil-Adlung, 2013: 36), where in principle SHI should serve as the main financial source and voluntary insurance, such as PHI, should be secondary in global terms (Fuenzalida-Puelma et al., 2013: 500-501).

A concern about this idea is that SHI may crowd out PHI making the mix unstable. The original observation of the crowding-out effect traces back to data arising from the expansion of Medicaid in the US between 1987 and 1992 (Cutler and Gruber, 1996). Since then, dozens of studies in the US reported the crowding-out effect, in which the expansion of public insurance programmes reduced the coverage of PHI, prevailed in the poor's Medicaid (Cutler and Gruber, 1996, Dubay and Kenney, 1997, Shore-Sheppard et al., 2000) and Children's SCHIP (Shone et al., 2008, Bansak and Raphael, 2007), and lasted for a long time (Gruber and Simon, 2008).

However, the modality of the mix in China is different from that of the US. The US public programmes like Medicaid, which provide comprehensive coverage, are a substitute for PHI; some of those eligible for the public programme drop PHI to join it (Cutler and Gruber, 1996). SHI in China, as in many low- or middle-income countries, emphasises universality but cannot provide comprehensive benefits coverage, therefore it is compatible with PHI which offers complementary coverage. Notwithstanding the different contexts, this study finds a similar pattern in China to that in the US: between 2004 and 2011, those with coverage under SHI were less likely to have PHI than those without SHI. It suggests that even if there is no such either-or choice between SHI and PHI, SHI still reduces, or indeed crowds out, the take-up of PHI.

A theory that explains the phenomenon is that the crowding-out effect is essentially the duplication of benefits, and is dependent on coverage of the public programme (Barros and Siciliani, 2012: 955-956). A universal and comprehensive public programme can completely crowd out the PHI market; it can also reduce its coverage to leave room for the development of PHI.

Taking the findings of this study together, the public-private mix does not appear to be a promising way to achieve UHC. Under universal but insufficient SHI coverage, the realisation of UHC, in theory, has to look to universal enrolment of complementary PHI or at least a tendency in this direction. However, this study finds that PHI's current prevalence is too low to substantially contribute to the progress of UHC. Dynamically, the growth of prevalence is also too slow to reach a qualitative change of its importance in health financing in the short term, and it would be even slower as SHI continues to expand. At this rate, realising UHC by engaging the private sector to complement the public sector is unlikely to happen.

Government interventions may help to break the impasse. The first possibility is changing the features of PHI. For example, in countries like Uruguay and Switzerland the governments mandate the purchase of PHI (Sekhri and Savedoff, 2005), and in the Netherlands and Chile, the pricing of some PHI products is income-related rather than risk-related (Enthoven and van de Ven, 2007, Sekhri and Savedoff, 2005). The second is defining the mandated benefits package. In the Netherlands, South Africa, and the US after recent health reforms, the government requires insurers to provide some basic packages that are open to everyone or to some government-qualified groups (Enthoven and van de Ven, 2007, Mills et al., 2012, White, 2012). Third, government may simply subsidise PHI purchase, such as in the US, Ireland, and recently China (Oberlander, 2012, Nolan, 2006, EY, 2016b). In fact, many heavily-regulated PHI products commonly receive subsidies as well (Enthoven and van de Ven, 2007, Sekhri and Savedoff, 2006).

A key rationale for government subsidies to PHI is that with the same coverage gain government can save money by shifting funds from public insurance to PHI subsidies, because government subsidies, if not the full price, encourage people to pay more for their insurance, thereby mobilising more private funds to finance healthcare (Musgrove, 2007: 174). First, however, this objective can also be achieved by partially-subsidised SHI schemes. China's NCMS and Rwanda's community-based health insurance are successful models, in which the governments contribute a large part of the public funds and the enrolees voluntarily contribute the rest, quickly raising national insurance coverage (Kutzin et al., 2016).

Second, importantly, as a crucial principle of UHC, it is problematic if government subsidises a health programme that damages equity (Nolan, 2006, Kutzin, 2013). Since PHI has been associated with unequal distributions in favour of the more affluent, subsidising PHI would be at the risk of in effect shifting money from the poorer to the better-off. Arguably, a well-designed subsidisation targeting poor people or poor regions could be put in place. However, the mechanisms through which PHI causes inequalities are multiple, as this study shows. Simply subsidising the poor to buy PHI cannot reduce the disparities in health resources that allow people in affluent areas to benefit more from PHI. Thus, without the strong assumptions such as spatially equally-distributed resources across the country and well-designed subsidisation in favour of the poor, government interventions to promote complementary PHI may in fact be detrimental to UHC.

Consequently, the role of PHI in the UHC project currently seems to be double-edged and potentially intractable. It indeed enhances overall coverage and access by providing its enrolees with benefits, but the benefits mainly flow to the more affluent groups, which is inconsistent with equity of coverage and access goals. Its relationship with SHI has decided that it would be hard to achieve UHC by expanding SHI as well as engaging PHI under the *laissez-faire* market, but government interventions would raise even more problems of rationality and equity.

8.3.3 Methodological contributions

This study's methodological contributions mainly relate to application of the CHNS dataset, which is very popular for studies of China's health. First, in the present study, three-level modelling – rarely used in the other related studies – is applied to most analyses. With the three-level structure, the model fits precisely into the observation-individual-community-nested relationship of the CHNS dataset. This is also a theoretically better solution for dealing with the unbalanced longitudinal data than a simple pooling strategy (Peugh and Heck, 2017). Moreover, this matches the sampling strategy of the CHNS very well, as it treats the community as the primary sampling unit (PSU). Because the CHNS does not provide any weight for research (Popkin, 2014), setting the PSU as a level in the modelling may help to improve the representativeness of the data.

Second, missingness is a considerable problem for the CHNS data, which consists of all kinds of missingness: wave non-responses/attrition, unit non-responses and item missingness (Carpenter and Plewis, 2011). Unlike most of the previous studies, which used the complete case analysis (CCA) that simply listwise excludes missing data, this study adopts the multiple imputation method to handle the problem. Additionally, to take into account within-individual correlation of the longitudinal data, this study uses the wide-form format to impute missing values for every individual in the five waves of the study. The sensitive test shows that the coefficients of the imputed model and the CCA model are basically consistent. This suggests that while multiple imputation does not significantly change conclusions, it takes advantage of more information from the available data than the CCA.

Finally, this study applies both the Heckman-probit model and the ZINB model to model health expenditure data, which were at best log-transformed and modelled by the Heckman-linear model or the two-part model in other related studies (Chen et al., 2009, You and Kobayashi, 2011, Liu et al., 2011a, Fang et al., 2012). However, these methods have also been criticised for their drawbacks by some academics (Linders and De Groot, 2006, Sileshi, 2006, Changyong et al., 2014). This study takes a new approach. Adopting the Heckman structure first, it transforms the continuous variable to a pair of binary variables, thereby circumventing the issues of heavily-skewed data and log-transformation. However, this is at the cost of information loss. To compensate for this loss, the study also adopts the ZINB model to treat expenditure as counts, an approach that has become increasingly popular but has not been used on the CHNS health expenditure data before this study, as far as the author knows. As a result, the two types of models are in general accord with each other, which suggests that the ZINB model would be a good choice for future studies.

8.4 Implications for policy making

Based on analyses of Chinese data, the conclusions of this study are hopefully useful for China's central and local government policy making on health financing. Additionally, as the world's most populous country and its second largest economy, the implications of this study are relevant for global development, especially for low- or middle-income countries that are seeking pathways towards UHC.

8.4.1 For domestic policy making

Will PHI help to complete the remaining steps towards UHC in China? There are three implications from this study.

First, achieving UHC through the public-private mix would be unlikely to happen in China's current policy context. Basically, the PHI market in China possesses the major features of a *laissez-faire* insurance market, such as voluntary enrolment, risk-related pricing, lack of mandated packages, no government subsidies (at least until very recently), and importantly the inequalities, as this study finds, that indicate insufficient regulations. On one hand, these features themselves automatically restrict PHI's growth in prevalence (Sekhri and Savedoff, 2006). On the other, competition from SHI schemes, which offer increasingly duplicated benefits at cheaper costs due to subsidisation (see Section 1.2.1), suppresses the take-up of PHI. As long as SHI continues to expand, the demand for PHI will correspondingly reduce, though SHI coverage has yet to be sufficient. Given its small population coverage and slow growth, if the current policies are not significantly changed, PHI is unlikely to substantially grow to address the gaps left by SHI.

Furthermore, as SHI gradually eats into PHI's space, the untapped potential of complementary PHI would diminish, and the market could substantially turn to the higher end, providing luxury benefits beyond the standards of UHC. China's economic inequality and PHI's pro-wealth enrolment are supposed to foster this trend. Consequently, the domestic PHI market would continue to grow, but the increase of premium income would hide the structural change under which complementary PHI may have been replaced by supplementary PHI. Even if UHC could be achieved in the future, it would be attributable to the exclusive contribution of SHI rather than the public-private mix of SHI and PHI.

Second, subsidising PHI is very likely to risk damaging equity in China. A tax-break policy has been piloted in some central cities such as Beijing and Shanghai. It allows up to ¥2400 (¥1≈ £0.11 or $0.14) per year individual income tax (IIT) deduction for purchasing qualified PHI products (EY, 2016a). However, not everyone has an equal chance of receiving the benefit. According to a report, only a small proportion of 770.4 million working population in China are paying IIT (Goldman Sachs, 2016). Some who do not pay IIT simply do not earn enough (less than ¥3500 per month), while more than 200 million people working in the informal sector or informally employed (Liang and Langenbrunner, 2013) are also unlikely to pay IIT, regardless of actual income. As a result, the typical beneficiaries of the IIT tax-break policy are urban higher-income, formal sector employees.

PHI has disproportionately benefited the wealthy and those living in more affluent areas, and the IIT tax-break policy would, if fully implemented, continue to increase PHI prevalence among them by reducing their financial burden of purchasing PHI. Since IIT is earmarked for nationwide redistribution, the current IIT deduction policy is in effect shifting money from poorer people and regions to subsidise wealthy urbanites. It is unlikely to be an efficient way of increasing insurance coverage either, because among the policy-targeting group, the prevalence of PHI is already higher than low-income and rural (inland) residents, who are in greater need of increasing insurance coverage but are not eligible for the IIT tax-break policy.

Third, the inequality of SHI may be easier to handle than that of PHI. For example, as this study finds, the government FMS had advantages over other schemes in promoting access and financial protection; the NCMS basically only worked in the rural areas, and they all tended to perform worse in the poorest rural inland areas than other areas. However, unlike PHI, SHI's problems have been well stated in the literature and clearly attributed to different contribution mechanisms and different administrative agencies among schemes (Liang and Langenbrunner, 2013), as well as local pooling and managing institutions (Meng et al., 2015) in China. In a word, it is fragmentation that causes SHI's compensation policies to vary scheme by scheme and county by county.

Recent times have seen a tendency to consolidate these fragmented SHI schemes, guided by the State Council (the central government)'s *Opinion on consolidating urban and rural residents' basic medical insurance* (State Council, 2016). Some areas have piloted a consolidation of the NCMS, URBMI[46] and UEBMI[47] in various modalities (Meng et al., 2015). Moreover, the privileged FMS has been gradually

[46] Urban Residents' Basic Medical Insurance, one of the urban SHI.

[47] Urban Employees' Basic Medical Insurance, one of the urban SHI.

scaled down by shifting its members to the UEBMI during the health reforms (Daemmrich, 2013).

Apart from these, there is little unequal prevalence of SHI as a whole at present, because it has approached universal population coverage well (Meng et al., 2012). In addition, because of income-related contributions and the subsidisation of local and central governments with pro-poor mechanisms (Yip et al., 2012, Liang and Langenbrunner, 2013) (see Section 1.2.1), SHI institutions are financially progressive; inequity reduction of SHI as a whole is well documented (Liu and Zhao, 2014, Zhou et al., 2014, Zhang et al., 2015). These arguments dispel the misgivings about inequity that result from subsidising SHI. In contrast, engaging PHI faces the dilemma between the slow growth of prevalence without subsidisation and the increase of inequity under subsidisation.

Taken all together, Chinese decision-makers may need to rethink whether it is beneficial for UHC to shift funds from public to private. According to the analysis above, compared to engaging PHI, continuously increasing funding for SHI to improve its generosity and consolidating fragmented SHI schemes to reduce inequality would be a conservative but sound path towards UHC. As previously stated, the prerequisites of putatively equitable PHI should be pro-poor subsidisation mechanisms at both the individual and aggregate levels, and government trying its best to distribute health resources more equally and enhance public-private cooperation in less developed areas. These requirements seem quite ambitious to government administration, however. Besides, stricter regulations such as government-defined benefit packages, mandatory risk-unrelated pricing, open enrolment and even mandatory purchase might be useful, according to international experience (Sekhri and Savedoff, 2006), but they are not what this study suggests, and make PHI very similar to SHI.

8.4.2 For global development

The WHO plays a leading role in technically supporting countries that have adopted UHC as a national aspiration in policy making and progress monitoring, in partnership with many organisations (WHO, 2016), including the World Bank, which provides technical assistance and capital financing to governments (World Bank, 2017). The WHO generally recognises PHI as a form of prepayment and pooling that is preferable to OOP payments, but warns that it will tend to lead to gaps in healthcare coverage unless there is extensive government regulation, including compulsory purchase and subsidisation (WHO, 2018). For countries with inadequate public financing, mostly low- and middle-income countries, World Bank authors have recommended a pluralistic multi-pillar healthcare insurance system with a primary public sector and a secondary private sector (van Duin, 2013: xix).

The lessons from China in this study may help these global development agencies to develop more informed policy advice concerning the role of PHI in the healthcare system and changes over time as mainstream UHC efforts focused on public financing are advanced. It may also be valuable for countries with similar economic development and healthcare institutional settings to China in their policy making.

One lesson of this study is that the PHI market is unlikely to grow sufficiently enough to fill the gaps left by SHI without direct policy interventions to encourage it. Economic growth may be a necessary condition for such growth, but it is not sufficient, as this study suggests. As one of many determinants, the growth of SHI reduces the take-up of PHI as the breadth, depth and height of the coverage it provides are enhanced. The crowding-out effect of public schemes as alternatives to PHI has been well documented (Cutler and Gruber, 1996, Gruber and Simon, 2008); where there is a complementary relationship between SHI and PHI, as long as the government uses the benefits of economic growth to increase all of the coverage dimensions of SHI, the demand for PHI to complement SHI reduces, so gaps may still exist.

Another lesson is that for countries with considerable spatial disparities, spatial inequalities in PHI enrolment and effectiveness are likely. As this study finds, controlling for individual/household characteristics, the inland and rural areas of China were commonly associated with lower PHI prevalence, and PHI was less effective in promoting access to healthcare in these areas than in the eastern and urban areas. These outcomes are, perhaps, related to limited insurance supply in poorer areas, since commercial insurers focus their marketing and investment strategies on the more affluent urbanised districts. In addition, poorer areas may have relatively limited healthcare supply and inefficient regulations, which weaken the effect of PHI on access. Accordingly, a focus on PHI as a means of enhancing coverage is likely to further deepen spatial inequalities in prevalence and access unless, for example, a combination of compulsory purchase and subsidies (on PHI purchase and healthcare supply) are used. Where PHI is identified as a promising route forward, technical assistance may be required to build domestic capacity to implement such regulations and ensure compliance.

8.5 Limitations

This study seeks to produce reliable results by carefully designing the research framework, using a reliable dataset, and employing suitable statistical techniques. Notwithstanding, there remain some limitations, most of which are associated with the dataset, the China Health and Nutrition Survey (CHNS). Furthermore, some other methods could have been applied to analyses, but this has not been done due to technical restrictions. Based on these limitations, the desirable next steps in the research agenda are suggested.

8.5.1 The range of time

Subject to the CHNS dataset, the study looked at the period between 2000 and 2011. The first SHI scheme was launched in 1998 (State Council, 1998). Because this study focuses on PHI in the context of the expansion of SHI in China, the 2000 data, next to the last CHNS survey wave in 1997, covers information about the beginning of the reformed SHI system well. However, the contemporarily available CHNS data when this research was undertaken ends at the 2011 wave. Since then, the PHI market continues to grow in terms of its premium income (China Insurance Regulatory Commission, 2014) and public funding for SHI is improving year on year as well (Meng et al., 2015).

It is regrettable, but unavoidable, to exclude these data from the study scope. At the beginning of this research in 2014-2015, I did not expect publication of the next wave of the CHNS data, the 2013/2015 survey, would be as delayed as it was. In a reply to my enquiry about this, the director of the CHNS informed me that the new data would come out in 2017. As it was still unavailable in September 2017, I could not afford to wait to include the new data in my study (the 2015 CHNS data were finally released in April 2018 and there were no 2013 data).

On the positive side, policies on health financing between 2011 and 2017 were largely a continuation of those reforms in the 2000s. On the one hand, reforming the SHI institutions and enlarging population coverage has been gradually replaced by benefits promotion since 2007 when the last SHI institution was introduced (Meng et al., 2015, Meng et al., 2012), and the focus of recent reforms has been mostly shifted to the delivery side (Yip and Hsiao, 2014). On the other hand, there have been few long-established substantive preferential policies on the PHI market (Xiang, 2014, EY, 2016a). The data from 2000 to 2011 provides abundant information for the study's purposes, and since the basic policy context remains unchanged, the results of this study are still relevant to current policy-making.

One alternative dataset of increasing popularity is the China Health and Retirement Longitudinal Study (CHARLS). However, its first nationwide sampling started in 2011, when the major scaling-up of SHI coverage was completed with a very small proportion of people uncovered (Meng et al., 2012). Accordingly, the dataset misses the information about the intense reforms of the 2000s, and is therefore particularly unsuitable for the evaluation of SHI's impact on the prevalence of PHI. Nonetheless, since the CHARLS has steadily published data every two years since 2011 and samples more comprehensively, it will be very useful for future research.

8.5.2 The effect of health insurance coverage

In the models employed by this study, the only variable about PHI is binary, indicating membership, either "on" or "off". The categorical SHI variable can be in effect broken down into three binary variables, too. The basic problem of these binary indicators is that they assume that the same type of health insurance programmes exert the same effect on the dependent variable.

SHI schemes are pooled and managed locally. In 2012, there were roughly 333 UEBMI schemes, 333 URBMI schemes and 2852 NCMS schemes (Meng et al., 2015). The compensation policies of the same type of SHI vary among counties and urban prefectures. For PHI, because it is generally pooled nationally, the spatial variation in compensation policies is small. However, as there are thousands of PHI products in China (Xiang, 2014), the across-product variation exists.

However, the binary variables are the choice that most previous studies have had to adopt (Zang et al., 2012, Lam and Johnston, 2012, Qin et al., 2014, Chai, 2014, Chau, 2010, Liu and Wang, 2012, Dong and Zhao, 2013, Yang, 2013, Yue and Zou, 2014), due to lack of detailed information about insurance policies in these popular datasets such as the CHNS. It seems difficult in practical terms for such large-scale household surveys to record the detailed PHI policy from every PHI member. Comparatively, it would be easier to collect data about SHI compensation policies, which should be aggregate data at the county level or the prefecture level. We hope to see the improvement in future datasets.

Notwithstanding the compromise, this study tried to reflect the variations in other approaches. First, multilevel modelling with the community at the highest level has basically taken into account all among-community variations including that of insurance policies. Second, the year dummies and the community development indexes can partly capture unobserved variation in insurance policies across time and among communities. Third, the study population is disaggregated according to major geo-economic factors, in order to directly compare the differences in effect of these insurance programmes across regions in China.

In terms of variations among PHI products, it is hoped that in the future, more specific information about PHI would be collected by surveys. Some information such as the types of PHI (complementary or supplementary, consumption or investment, whether covering outpatient care, etc.), the insurer's name, the cap, the deductibles, and the cost-sharing proportion would be valuable for research.

8.5.3 The indicators of utilisation and financial protection

The utilisation of healthcare can be indicated by its frequency and intensity of use (Hou et al., 2014). In the CHNS dataset, there are specific variables indicating the use of outpatient care, the use of inpatient care, and the length of hospital stay. However, for the latter two, the numbers of valid observations are too small to be computationally sufficient for the multilevel modelling of longitudinal data and disaggregation. After a trade-off, I combined the use of outpatient care and inpatient care to form the dependent variable, as opposed to self-healthcare and no utilisation. Admittedly, this method does not provide full information about frequency and especially intensity.

A similar situation occurs with the dependent variables of financial protection. The OOP payment for healthcare is a commonly-used indicator of financial risk in the literature (Van Doorslaer et al., 2007, Fang et al., 2012, You and Kobayashi, 2011). Besides this, many international studies embrace the incidence of catastrophic health expenditure (Xu et al., 2007). Although the working definitions of catastrophic health expenditure vary among studies, none of them is calculatable using the CHNS dataset (see Section 3.5.3).

However, the influence of this on the realisation of the research purpose should be limited. The first reason is that the selected variables in this study are still widely accepted and have been used in a number of studies. Second, importantly, the focus of this study is PHI (SHI is of less importance), rather than exact measurements of utilisation or financial risk, which are not research objects *per se*, but serve as tools for indicating the effects of health insurance. Notwithstanding this, existing and future studies on PHI using other indicators would be valuable complements.

8.5.4 Modelling health expenditure

Finally, the multilevel modelling method is not employed to model financial risk. This is a compromise between feasibility and precision. Abandoning the multilevel structure undoubtedly reduces the capability of the model in comprehending the data structure. However, this compromise should be acceptable, since a number of previous studies on health expenditure based on Chinese survey data, simply adopted individual-level models (Chen et al., 2009, You and Kobayashi, 2011, Liu et al., 2011a, Fang et al., 2012). In this study, in the absence of the multilevel structure, the method of cluster-robust standard errors is applied to deal with the within-individual correlation of longitudinal data. Moreover, a group of community-level indexes indicating the health-related development of the community are included, to provide the models with information about the communities that individuals reside in.

Apart from this, modelling health expenditure would have been improved by employing the Heckman-Poisson model; however, it was not built in Stata until the recently-released version 15. In theory, this model can overcome the selectivity of healthcare users with the two-equation structure, while it properly handles the non-normal distribution of health expenditure data by assuming a Poisson distribution. Therefore, it should be able to provide more information than the Heckman-probit model that this study uses. There is a user-written Heckman-Poisson model command "*ssm*" based on an algorithm of generalized linear latent and mixed models (*gllamm*) (Miranda and Rabe-Hesketh, 2005), but this failed to converge with the study population when I attempted it. This study uses the ZINB model instead, as it can directly estimate health expenditure data (Lambert, 1992, Hall, 2000) to complement the Heckman-probit model, trying to provide as much information as possible. Nonetheless, if Stata 15 is available, the Heckman-Poisson model deserves to be tried.

Notwithstanding these efforts, admittedly, information loss happens during the transformation of the health expenditure variable. Basically, health expenditure is originally a continuous variable, which means it could have an infinite number of values, while they must be non-negative. For the Heckman-probit model, transforming the continuous variable into two binary variables in effect reduces the potentially infinite number into three, undoubtedly losing substantial information that the expenditure data contain, which I have recognised at the beginning of Chapter seven. To compensate the loss, I additionally used the ZINB model, which treats the health expenditure data as counts. So does the potentially useful Heckman-Poisson model as mentioned above. However, in a count model, the health expenditure data are required to be discrete integers and hence have a finite number of values within a certain range (Meyer et al., 1985). Therefore, although this is better than the binary variable, information is also lost when the potentially infinite number of values are integrated into a finite number of values. The loss is especially serious when the range of values is small, which means only a small number of integers that belong to this range are modelled.

8.6 Conclusion

This study demonstrates that PHI is distributed unequally in favour of those in higher socioeconomic groups and more affluent areas. PHI has a positive effect on access to healthcare for those in need, particularly so for those who live in more affluent districts – such that, compared to those without PHI, those with PHI in need of healthcare used it more frequently; however, this was especially the case in the more affluent eastern and urban areas; and this effect relied on the presence of SHI. Additionally, PHI prevalence and its effect on access to healthcare varied among communities more in rural areas than urban areas, and PHI tended to increase a community's average access to healthcare and financial protection in the east, but reduce access in the inland areas.

These findings help to deepen the insights into the inequalities that arise from PHI, which are extended from those between individuals of different socioeconomic status to those between geo-economic regions; from those in PHI prevalence to those in its effectiveness; and from those upon the single PHI enrolee to those upon the whole community. It is shown that PHI prevalence, its effectiveness and even its impacts on a community are considerably unequal, invariably in favour of the more affluent individuals or areas. In a word, the inequalities caused by PHI are not single-faceted but systematic and pluralistic, and they require strict regulation by government.

This study also shows that from 2000 to 2004 and afterwards, as SHI coverage expanded to cover more of the population against more of the cost of healthcare, and for more treatment types, individuals with coverage under SHI became less likely to hold a PHI product than those without SHI coverage, suggesting that the use of PHI as a means of contributing to UHC efforts is unlikely to be realised without additional government interventions aimed at its promotion. Such interventions – most likely, efforts to encourage purchase such as making it compulsory and enhancing the ability to pay through subsidies (or tax relief) – need domestic capacity to implement and would have the effect of making PHI very similar to SHI in many respects. Hence, the benefit of doing this from a policy perspective, i.e. in the context of strong and expanding SHI programmes, is perhaps open to question – both in China and elsewhere.

Appendix A: The summary of the literature review

Study	*Data Source*	*Sampling years*	*Sampling areas*	*Level of Data*	*Principal Method*	*Evidence for*	*Results*
(Liu et al., 2011b)	CHNS	2000, 2004, 2006	9 provinces	Individual	Logistic models with difference in difference estimator, without propensity score matching	Prevalence	NCMS enrolment was positively associated with adults' PHI enrolment compared to no SHI, especially in higher income group, but negatively associated with children's PHI enrolment, especially in lower income groups.
(Liu et al., 2014)	Multi-centre retrospective study	2010-2013	Shanghai	Individual	Chi-square tests that compare PHI enrolment among different SHI status	Prevalence	Coverages of PHI in NCMS, URBMI, UEBMI groups were lower than the uninsured group.
(Ying et al., 2007)	Household survey	2004	4 cities of 2 provinces	Individual	Random effect logistic models	Prevalence	Employees in private enterprises or the self-employed were positively associated with the probability of purchasing PHI covering major catastrophic diseases.
(Lam and Johnston, 2012)	Phone survey	2010	Shenzhen	Individual	Multivariate logistic models	Prevalence, Access	Migrants were more associated with being uninsured or having PHI only. None of SHI, PHI or both were associated with use of outpatient care in 30 days or inpatient care in 12 months. No different in any kind of health insurance's

							association with healthcare utilisation between migrants and local registrants.
(Fang et al., 2012)	Phone survey	2011	Beijing, Shanghai and Xiamen	Individual	Logistic models	Prevalence, financial protection	Urban residency was not significantly associated with PHI purchase. PHI was positively associated with the occurrence of gross medical expense over 1000 yuan and the occurrence of OOP spending over 1000 and over 5000.
(Yue and Zou, 2014)	CHARLS	2011	28 provinces	Individual	Bivariate probit models for both PHI enrolment and pension scheme enrolment	Prevalence	Urban population (registrants of urban *hukou*) was more associated with having PHI.
(Jin et al., 2016)	CHARLS	2011 2013	28 provinces	Individual	Multinomial logistic models for five insurance status	Prevalence	SHI (NCMS, URBMI, UEBMI) enrolment was negatively associated with PHI enrolment compared to no SHI. After aggregating, the association only happened in urban areas. Compared to NCMS, URBMI was negatively associated with PHI enrolment, but UEBMI and no SHI were associated with PHI enrolment. Compared to urban residents, the rurally-registered were negatively associated with having PHI, or both SHI and PHI, but also negatively associated with being uninsured. Compared to locals, migrants were more associated with being

							multiple insured, insured by PHI or completely uninsured.
(Hou and Zhang, 2017)	CHNS	2004 - 2011	9 provinces	Individual	Logistic models with difference in difference estimator, without propensity score matching	Prevalence	The expansion of urban URBMI (focused on unemployed), indicated by interaction between years and treatment group (areas with high proportion of children and elderly), had not significantly correlation with PHI purchase.
(Yang, 2013)	CHNS	2004, 2006, 2009	9 provinces	Individual	Probit models for health services use and linear probability models for calculating Concentration Indices	Access	Based on the rural sample, compared to no insurance, enrolment of PHI was negatively correlated with using outpatient care, but positively correlated with using preventative care.
(You and Kobayashi, 2011)	CHNS	2004	9 provinces	Individual	Heckman selection models that select healthcare users and then model their OOP payments	Access, financial protection	Higher income earners were both more associated with to having PHI and using preventative care than lower income earners.
(Qin et al., 2014)	State Council URBMI Household Survey	2007-2010	9 cities	Individual	Instrumental variable regression, using the community-year level participation rate of each insurance programme among the non-migrant	Access	PHI had no significant association with OOP payments.

					population as the instrumental variable		
(Chau, 2010)	NHSS	2003	31 provinces	County	Multivariate linear models for the number of outpatient visits, the number of inpatient visits and per capita annual medical expenditure	Access, financial protection	The percentage of individuals in a rural county having PHI had a positive relationship with the number of outpatient visits per 1000 in 2-week; but did not have a significant relationship with the number of inpatient visits per 1000 in 52-week. PHI was not associated with per capita annual medical expenditure.
(Zhu et al., 2008)	Survey in elementary school	2005	Pinggu district in Beijing	Individual	Chi-square tests that compare health access indicators among different insurance status	Access	Comparing among PHI, NCMS and no insurance, the PHI group had lower parental perceptions of children's difficulty in access to healthcare and foregone care, but had no difference in outpatient visits and satisfaction.
(Wang et al., 2016)	CHARLS	2011, 2013	28 provinces	Individual	Heckman selection models that selects awareness of healthcare provider ownership and model utilisation for only outpatient users	Access	Compared to no insurance, enrolment of (basic) PHI was more associated with using outpatient care, awareness of ownership of healthcare provider, and using healthcare in public hospitals; however, supplemental health insurance had no correlation with utilisation or choice between public and private providers.
(Wang et al., 2010)	An urban hospital records; a	Urban: 2003; rural: 2005	Urban: Beijing;	Individual	Linear regression directly on health expenditure data	Financial protection	PHI was associated with increased (total) medical expenditure compared to regular insurance, an

	survey in 101 villages		rural: 5 provinces				outdated insurance with limited coverage of medicine and services.
(Xu et al., 2015)	NHSS	2008, 2013	Rural Shaanxi province	Individual	Decomposition based on the logistic models for the incidence of catastrophic health expenditure indicated by OOP payments over 40% of the household capacity to pay	Financial protection	Absence of PHI was associated with the occurrence of catastrophic health expenditure in 2008 and 2013, so was absence of SHI. Absence of PHI were more concentrated among the worse off (negative concentration index).
(Chen et al., 2012)	NHSS	2002, 2007	Gansu province	Individual	Kakwani index of progressivity of healthcare payments on gross income	Financial protection	In 2002, in both cities and villages, PHI was progressive; compared to rural areas, PHI was more progressive in urban areas. In 2007, the extent of progressivity was less in cities, but more in villages than 2002; PHI was less progressive in urban areas than rural areas.
(Chen et al., 2014)	NHSS	2002, 2007	Heilongjiang province	Individual	Kakwani index of progressivity of healthcare payments on gross income	Financial protection	In 2002, PHI was regressive in cities, while it was progressive in villages; in 2007, PHI was progressive in cities, while it was regressive in villages.
(Li, 2009)	State statistics	2002-2007	3 provinces	Provincial	Linear models	Prevalence	PHI premium income was positively correlated to covered population of all SHI schemes

(Lv, 2013)	State statistics	2005-2011	Nationwide	Provincial	Degree of coupling referring to coupling theory in Physics	Prevalence	There was coupling relationship with moderate strength between the PHI market (indicated by income, expenditure, claim ratio, etc.) and rural NCMS development (indicated by income, expenditure, ratio of income and expenditure, etc.).
(Wang, 2011)	State statistics	2002-2009	30 Provinces	Provincial	Dynamic panel models with a first order lag	Prevalence	Income of UEBMI was positively associated with PHI premium income.
(Wang, 2009)	State statistics	2000-2007	Nationwide	Provincial	Linear models	Prevalence	Income of UEBMI and URBMI was positively associated with PHI premium income.
(Zheng and Hua, 2013)	State statistics	2005-2010	Nationwide	Provincial	Degree of Coordination based on the composite system synergy degree model	Prevalence	The degree of coordination between total SHI funding and PHI premium income was moderate in most provinces, good in four provinces (three in the eastern coast), and bad in four provinces (all in central or west).
(Yuan et al., 2014)	CHNS	1989-2009	9 provinces	Individual	Logistic models for PHI enrolment, and fixed effect models and instrumental variable regression for total health expenditure	Prevalence, financial protection	NCMS and other public health insurance were negatively associated with PHI enrolment compared to no SHI. PHI was associated with increased total health expenditure for the whole. PHI was associated with increased total health expenditure more in cities than villages.
(Xu et al., 2013)	CHNS	2004 2006 2009	9 provinces	Individual	Probit models with difference in difference estimator, without	Prevalence	NCMS was negatively associated with PHI enrolment between 2004 and 2006, but was

					propensity score matching		positively associated with PHI enrolment between 2006 and 2009, compared to no SHI.
(Xu, 2007)	Household survey	2006	Shanghai municipality	Individual	Linear models for logged expenditure on PHI	Prevalence	In the low-income group and middle-high income group, SHI (all type) enrolment was negatively associated with PHI purchase compared to no SHI, while in the low-middle income group, the correlation was positive.
(Liu and Wang, 2012)	CHNS	2000 2004 2006	9 provinces	Individual	Bivariate probit models with partial observability	Prevalence	Both urban SHI schemes and NCMS enrolments were associated with PHI enrolment compared to no SHI. In urban areas students were more associated with having PHI than non-students, while in rural areas this relationship disappeared.
(Qu and Wang, 2010)	CHNS	2006	9 provinces	Individual	Bivariate probit models for both PHI enrolment and NCMS enrolment	Prevalence	NCMS was associated with PHI enrolment compared to no SHI. Rural residents in eastern provinces were more associated with buying PHI than their counterparts in inland China.
(Zhu and Gui, 2014)	State statistics	2003-2012	Nationwide	Provincial	Fixed effects models with per capita outpatient expenditure as the instrumental variable	Prevalence	The average compensation from UEBMI and URBMI was positively associated with PHI premium income
(Wang et al., 2015)	State statistics	2007-2013	31 provinces	Provincial	Fixed effects models	Prevalence	The percentage of enrolment of all SHI schemes was positively associated with PHI premium income. PHI premium income was greater in rich

							eastern provinces than central or west inland provinces
(Suo et al., 2015)	State statistics	2004-2013	31 provinces	Provincial	Linear models	Prevalence	PHI development, indexed by insurance penetration, insurance density and market concentration rate, was more likely to have positive correlations with richness of public health resources, indicated by the number of physicians (per 1000 people) and beds (per 1000 people), in eastern provinces than central and western provinces
(Zhu and Yu, 2015)	Individual survey	2010	Tianjin municipality	Individual	Probit models	Prevalence	No SHI was negatively associated with the willingness to buy PHI compared to all SHI schemes, among which no difference was found. Under the incentive of income tax break migrants were negatively associated with willingness to buy PHI compared to local residents. Government officials were negatively associated with willingness to buy PHI compared to others.
(Dong and Zhao, 2013)	Household survey	2012-2013	5 cities	Individual	Logistic models	Prevalence	Those working in private and unformal sectors were more associated with buying PHI than those working in formal sectors.
(Zhu and Wang, 2016)	Individual survey	2010	Tianjin municipality	Individual	Heckman-probit models that select willingness to buy PHI	Prevalence	Coverage of SHI was positively associated with the willingness to buy PHI, compared to no SHI.

					and then model the level of expenditure on PHI		
(Chai, 2014)	CHARLS	2008	2 provinces	Individual	Logistic and multi-nominal models for types of healthcare	Access	PHI, and other SHI schemes, were associated with utilisation of any kind of healthcare, compared to NCMS, but PHI was not associated with use of formal health care, compared to self-care.
(Yao et al., 2012)	Questionnaire survey	2011	Dongguan city	Individual	Chi-square tests that compare utilisation among different health insurance status	Access	PHI enrolees used less community health services than SHI schemes' enrolees. But the younger, higher-educated and richer used less services as well.
(Chai, 2013)	CHARLS	2008	2 provinces	Individual	Two-part models that select utilisation at first and then model logged health expenditure	Access, financial protection	For the whole population, PHI and SHI had a positive relationship with using inpatient care in last one year or outpatient care in last month, but had a significant negative interaction between them. In urban areas, both increases were significant and negative interaction was not significant; in rural areas, all were insignificant. PHI was associated with increased total health expenditure in the whole population. This effect only happened in rural areas, but did not in urban areas.

(Wang, 2012)	State statistics	2006-2010	Nationwide	Provincial	Fixed effects models for the average length of hospitalisation	Access	The depth of PHI, premium income over GDP, was positively associated with the average length of hospitalisation. But PHI depth's interaction with the coverage of urban SHI, the percentage of regional SHI enrolees, was significantly positive.
(Li et al., 2016)	Household survey	2014	Three cities in Sichuan province	Individual	Logistics models	Access	Both SHI and PHI were associated with using inpatient care compared to no insurance.
(Jiao, 2015)	CHNS	2000, 2004, 2006, 2009	9 provinces	Individual	logistic and linear models with difference in difference estimator, without propensity score matching	Access, financial protection	Between 2000 and 2004, PHI was positively associated with utilisation of preventative care and length of inpatient care compared to no PHI. Between 2006 and 2009, it was only associated with use of preventative care. 2000-2004, PHI was positively associated with the proportion of OOP payment for treatment. 2000-2004 and 2006-2009, PHI was negatively associated with the proportion of OOP payment for preventative care. 2000-2004, PHI was positively associated with high-income people's proportion of OOP payment for treatment, but negatively associated with that for preventative care. 2006-2009, PHI was negatively associated with both low-income and high-income's proportion of OOP for preventative care.

(Zang et al., 2012)	State Council URBMI Household Survey	2007, 2008	9 cities	Individual	Probit models	Access	There was a positive relationship between PHI enrolment and using inpatient care in last one year, but no significant relationship with use of outpatient care in last two weeks.
(Zeng et al., 2017)	Chinese longitudinal Healthy Longevity Survey(CLHLS)	2011-2012	23 provinces	Individual	Linear models	Financial protection	PHI had no significant association with OOP expenditure; but PHI as the main payment method was negatively associated with OOP expenditure.
(Wang and Wang, 2017)	Questionnaire survey	2014	8 provinces	Individual	Chi-square tests that compare the incidence of catastrophic health expenditure indicated by OOP payments over 40% of the household capacity to pay between PHI enrolment status	Financial protection	There was no difference between PHI enrolment and the incidence of catastrophic health expenditure.
(Li et al., 2012c)	NHSS	2003, 2008	Rural Xinjiang province	Individual	Kakwani index	Financial protection	Kakwani of health financing was 0.25 in 2003 and 0.20 in 2008, suggesting that PHI was pro-rich, but the extent reduced in 2008.
(Liu et al., 2013)	Third Corps Survey	2010	Xingjiang Corps	Individual	Aronson-Johnson-Lambert Redistributive effect	Financial protection	PHI's redistributive effect was negative but very small, suggesting that PHI's contribution to redistribution was very limited.

(Cui et al., 2016)	State statistics	2006-2012	31 provinces	Provincial	Fixed effects models	Financial protection	Per-capita PHI premium spending had a significantly negative relationship with average medical expenditure.

Appendix B: Model sensitivity tests

Comparing the complete three-level analytical model on PHI prevalence and the same model excluding the group of demographic variables and the same model excluding the group of socioeconomic variables, the profiles of their outcomes are very similar, especially the effects of the key independent variables, i.e. health insurance variables (Table A2.1). It suggests that the models for PHI prevalence appear to be robust.

Table A2.1 Test on the models on PHI prevalence

Model	*Analytical model*	*Test model 1*	*Test model 2*
	Coefficient (S.D.)		
Year	Reference = 2000		
2004	-2.08(0.11)***	-2.07(0.11)***	-2.01(0.11)***
2006	-2.08(0.11)***	-2.09(0.11)***	-1.98(0.10)***
2009	-2.05(0.10)***	-2.07(0.10)***	-1.89(0.10)***
2011	-1.86(0.11)***	-1.90(0.11)***	-1.69(0.10)***
Age	0.05(0.01)***		0.05(0.01)***
Age^2	-5.85e-4(0.00)***		-6.82e-4(0.00)***
Gender	-0.06(0.06)		0.02(0.06)
Chronic diseases	0.06(0.07)		0.06(0.07)
Household income	0.20(0.03)***	0.20(0.03)***	
Household size	-0.08(0.02)**	-0.08(0.02)**	
Education	Reference = no or primary school		
Middle or tech	0.22(0.07)**	0.36(0.07)***	
University	0.40(0.10)***	0.54(0.10)***	
Working	0.19(0.07)**	0.35(0.06)***	
Hukou	-0.51(0.12)***	-0.51(0.12)***	
SHI	Reference = no SHI		
FMS	1.81(0.08)***	1.75(0.07)***	2.03(0.08)***
Urban SHI	0.60(0.11)***	0.58(0.11)***	0.77(0.11)***
NCMS	1.30(0.09)***	1.30(0.09)***	1.23(0.10)***
Aggregate variables			

East	0.85(0.16)***	0.85(0.16)***	1.02(0.17)***
Urban	1.05(0.18)***	1.06(0.18)***	1.45(0.18)***
Population	-0.04(0.05)	-0.05(0.05)	-0.04(0.05)
Social services	-0.02(0.01)ᵻ	-0.02(0.01)ᵻ	-0.02(0.01)*
Health infrastructure	0.05(0.02)**	0.05(0.02)**	0.05(0.02)**
Random effect: Variance (S.D.)			
Community-level	0.87(0.13)***	0.88(0.14)***	1.05(0.16)***
Individual-level	0.32(0.13)*	0.32(0.13)*	0.37(0.13)**
Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,745. Significance values: ᵻp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.			

In following Table A2.2, while the outcomes of the analytical model for healthcare utilisation and the test models excluding demographic and socioeconomic variables, respectively (Test model 3 and Test model 5), are mostly similar, the most visible difference occurs between the analytical model and the model excluding demographic variables and current health status (Test model 4). Removing current health status strengthens the effects of most individual variables as well as the random effects at the two levels, because of the strong explanatory power of the health status for utilisation. However, although substance has changed, the conclusions derived from the models barely change, especially on the effects of health insurance schemes, because the significances and signs are basically maintained. In sum, it suggests that the findings related to PHI and SHI from the analytical models should be robust.

Table A2.2 Test on the model on healthcare utilisation

Model	*Analytical model*	*Test model 3*	*Test model 4*	*Test model 5*
Coefficient (S.D.)				
Year	Reference = 2000			
2004	0.62(0.09)***	0.64(0.09)***	0.88(0.07)***	0.62(0.09)***
2006	0.72(0.08)***	0.78(0.08)***	0.75(0.07)***	0.72(0.08)***
2009	0.63(0.09)***	0.74(0.09)***	0.80(0.08)***	0.61(0.09)***
2011	0.60(0.09)***	0.75(0.09)***	0.71(0.08)***	0.58(0.09)***
Age	0.02(0.00)***			0.02(0.00)***
Gender	-0.17(0.04)***			-0.22(0.04)***

Chronic diseases	0.50(0.05)***			0.51(0.05)***
Health status	4.22(0.06)***	4.35(0.05)***		4.23(0.06)***
Household income	-0.01(0.02)	-0.01(0.02)	-0.02(0.02)	
Household size	0.01(0.02)	-0.01(0.02)	-0.03(0.01)ᵻ	
Education	Reference = no or primary school			
Middle or tech	-0.10(0.05)ᵻ	-0.39(0.05)***	-0.67(0.04)***	
University	-0.10(0.12)	-0.47(0.12)***	-0.77(0.08)***	
Working	-0.21(0.05)***	-0.47(0.04)***	-0.71(0.03)***	
Hukou	0.07(0.07)	0.06(0.07)	-0.04(0.06)	
SHI	Reference = no SHI			
FMS	0.31(0.10)**	0.43(0.10)***	0.52(0.08)***	0.26(0.10)*
Urban SHI	0.10(0.08)	0.16(0.08)*	0.29(0.06)***	0.06(0.08)
NCMS	0.16(0.07)*	0.17(0.07)*	0.26(0.06)***	0.16(0.07)*
PHI	0.13(0.12)	0.09(0.12)	0.18(0.08)*	0.11(0.12)
Aggregate variables				
East	-0.25(0.06)***	-0.20(0.06)**	-0.10(0.07)	-0.27(0.07)***
Urban	-0.23(0.09)*	-0.15(0.09)	-0.06(0.09)	-0.26(0.09)**
Health infrastructure	-0.03(0.01)*	-0.02(0.01)*	-0.02(0.01)*	-0.03(0.01)*
Transportation	-0.01(0.01)	-0.01(0.01)	-0.02(0.01)*	-0.01(0.01)
Economic activity	0.00(0.01)	0.00(0.01)	0.02(0.01)**	0.00(0.01)
Random effect: Variance (S.D.)				
Community-level	0.10(0.02)***	0.10(0.02)***	0.18(0.02)***	0.10(0.02)***
Individual-level	0.49(0.08)***	0.51(0.08)***	0.86(0.05)***	0.49(0.08)***
Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,745. Significance values: ᵻp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.				

The following Table A2.3 and Table A2.4 compare the Heckman analytical models and the ZINB analytical models on the financial risk with their corresponding test models, respectively. The outcomes suggest that excluding demographic variables or socioeconomic variables make slight change to substance of the effects of remaining variables, but their significance and signs almost hold. They suggest that both the Heckman model and the ZINB model are robust.

Table A2.3 Test on the Heckman model for financial risk						
Model	*Analytical model*		*Test model 6*		*Test model 7*	
Equation	>50%	>90%	>50%	>90%	>50%	>90%
Coefficient (S.D.)						
Year	Reference = 2000					
2004	0.02(0.07)	-0.05(0.09)	0.01(0.07)	-0.06(0.09)	0.03(0.07)	-0.04(0.02) ǂ
2006	-0.03(0.07)	-0.20(0.09)*	-0.04(0.07)	-0.20(0.09)*	-0.02(0.07)	-0.19(0.09)
2009	0.10 (0.08)	-0.07(0.10)	0.09(0.08)	-0.07(0.10)	0.10(0.07)	-0.06(0.10)
2011	0.06(0.08)	0.05(0.10)	0.05(0.08)	0.05(0.10)	0.06(0.08)	0.06(0.10)
Age	-0.00(0.00) ǂ	-0.00(0.00)			-0.00(0.00)	-0.00(0.00)
Gender	-0.00(0.03)	0.06(0.05)			-0.02(0.03)	0.04(0.04)
Chronic diseases	0.18(0.04)***	0.19(0.05)***			0.19(0.04)***	0.20(0.05)***
Household income	0.02(0.02)	0.02(0.02)	0.02(0.02)	0.03(0.02)		
Household size	-0.03(0.01)**	-0.03(0.01) ǂ	-0.03(0.01)**	-0.03(0.01) ǂ		
Education	Reference = no or primary school					
Middle or tech	0.05(0.04)	0.06(0.06)	0.07(0.04)*	0.08(0.05)		
University	-0.02(0.08)	0.09(0.11)	-0.00(0.08)	0.12(0.11)		
Working	-0.18(0.05)***	-0.24(0.06)***	-0.17(0.04)**	-0.23(0.05)***		
Hukou	-0.03(0.06)	0.05(0.07)	-0.04(0.06)	0.04(0.07)		
SHI	Reference = no SHI					
FMS	-0.39(0.07)***	-0.20(0.10) ǂ	-0.38(0.07)***	-0.19(0.10) ǂ	-0.35(0.07)***	-0.18(0.10) ǂ
Urban SHI	-0.20 (0.06)**	-0.08(0.08)	-0.19(0.07)**	-0.07(0.08)	-0.17(0.06)**	-0.07(0.08)
NCMS	-0.26(0.05)***	-0.21(0.07)**	-0.26(0.05)***	-0.20(0.07)**	-0.27(0.05)***	-0.21(0.07)**
PHI	0.02(0.08)	0.15(0.12)	0.02(0.08)	0.14(0.12)	0.02(0.08)	0.14(0.12)
Aggregate variables						
East	0.11(0.04)**	0.07(0.06)	0.13(0.04)**	0.08(0.07)	0.14(0.04)**	0.09(0.06)

Urban	-0.05(0.06)	-0.04(0.07)	-0.05(0.06)	-0.04(0.07)	-0.01(0.05)	-0.02(0.06)
Health infrastructure	0.01(0.01)	0.00(0.01)	0.01(0.01)ƚ	0.01(0.01)	0.02(0.01)*	0.01(0.01)
Transportation	0.02(0.01)*	0.02(0.01)	0.02(0.01)*	0.02(0.01)ƚ	0.02(0.01)**	0.02(0.01)ƚ
Economic activity	0.01(0.01)	0.01(0.01)	0.01(0.01)	0.01(0.01)	0.01(0.01)	0.01(0.01)
Social services	0.01(0.01)ƚ	0.01(0.01)	0.01(0.01)ƚ	0.02(0.01)	0.02(0.01)*	0.02(0.01)
Population	-0.03(0.02)*	-0.04(0.02)ƚ	-0.03(0.02)*	-0.04(0.02)ƚ	-0.03(0.02)*	-0.04(0.02)ƚ

Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,745.

Significance values: ƚp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.

The results of the selection equations are not presented.

Table A2.4 Test on the ZINB for OOP health payments

Model	*Analytical model*		*Test model 8*		*Test model 9*	
Equation	%Zero	Count	%Zero	Count	%Zero	Count
Effect	Coefficient (S.D.)					
Year dummies	Reference = 2000					
2004	-1.65(0.11)***	-0.16(0.23)	-1.63(0.10)***	-0.18(0.26)	-1.65(0.11)***	-0.15(0.22)
2006	-1.51(0.12)***	-0.49(0.24)ƚ	-1.51(0.12)***	-0.49(0.26)ƚ	-1.51(0.12)***	-0.47(0.26)ƚ
2009	-1.53(0.14)***	-0.29(0.25)	-1.54(0.14)***	-0.32(0.25)	-1.52(0.15)***	-0.30(0.27)
2011	-1.26(0.15)***	0.129(0.27)	-1.30(0.14)***	0.11(0.29)	-1.26(0.14)***	0.08(0.29)
Age	-0.00(0.00)	-0.00(0.01)			-0.00(0.00)	0.00(0.00)
Gender	0.18(0.06)**	0.17(0.11)			0.19(0.06)**	0.11(0.10)
Chronic diseases	-0.50(0.07)***	0.49(0.11)***			-0.51(0.07)***	0.52(0.11)***
Household income	-0.00(0.04)	0.04(0.04)	-0.01(0.04)	0.05(0.05)		
Household size	0.04(0.02)ƚ	-0.03(0.03)	0.05(0.02)*	-0.04(0.04)		

Education	Reference = no or primary school					
Middle or tech	0.05(0.07)	0.03(0.11)	0.13(0.07) ǂ	0.04(0.11)		
University	-0.07(0.15)	0.16(0.26)	0.05(0.15)	0.15(0.25)		
Working	0.03(0.08)	-0.56(0.14)***	0.13(0.07)	-0.58(0.11)***		
Hukou	0.13(0.09)	0.06(0.16)	0.13(0.10)	0.02(0.16)		
SHI	Reference = no SHI					
FMS	0.78(0.17)***	-0.17(0.21)	0.75(0.17)***	-0.12(0.21)	0.73(0.17)***	-0.17(0.22)
Urban SHI	0.23(0.10)*	-0.11(0.17)	0.21(0.10)*	-0.08(0.17)	0.18(0.10) ǂ	-0.10(0.16)
NCMS	0.27(0.11)*	-0.22(0.16)	0.28(0.10)**	-0.19(0.16)	0.31(0.10)**	-0.21(0.16)
PHI	-0.17(0.18)	0.28(0.30)	-0.18(0.18)	0.25(0.30)	-0.19(0.18)	0.25(0.30)
Utilisation	-4.26(0.09)***	1.27(0.10)***	-4.30(0.09)***	1.31(0.11)***	-4.25(0.09)***	1.29(0.11)***
Health status	-4.25(0.10)***		-4.31(0.10)***		-4.26(0.10)	
Aggregate variables						
East	0.01(0.07)	0.16(0.11)	-0.03(0.07)	0.17(0.11)	-0.02(0.07)	0.17(0.10)
Urban	0.04(0.08)	0.01(0.16)	0.01(0.08)	0.01(0.17)	-0.02(0.08)	0.03(0.15)
Health infrastructure	-0.06(0.01)***	0.00(0.02)	-0.06(0.01)***	-0.00(0.02)	-0.06(0.01)***	0.01(0.02)
Transportation	-0.03(0.01) ǂ	0.04(0.02) ǂ	-0.03(0.01)*	0.04(0.02)	-0.03(0.01)*	0.04(0.02) ǂ
Economic activity	0.01(0.01)	0.00(0.02)	0.01(0.01)	0.00(0.02)	0.01(0.01)	0.01(0.02)
Social services	-0.01(0.01)	0.04(0.02)*	-0.01(0.01)	0.05(0.02)*	-0.01(0.01)	0.05(0.02)*
Population	-0.08(0.03)**	-0.08(0.05) ǂ	-0.09(0.03)**	-0.09(0.05) ǂ	-0.08(0.03)**	-0.08(0.05) ǂ
Data source: CHNS (2000, 2004, 2006, 2009, 2011); N = 80,745. Significance values: ǂp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.						

Appendix C: The full models based on data excluding the year 2000

For simplicity, Table 5.10 in Chapter 5 only shows the result about SHI schemes, whose effects on PHI enrolment experience a dramatic reversal after excluding the 2000 data from the whole. This appendix expands the table to provide full information about the models based on data excluding 2000, in order to scrutinise effect changes of other independent variables

Coefficients of most these independent variables are generally maintained at the similar level after excluding the 2000 data (Table 5.10). One of the most visible variation happens to age, which loses significance, plausibly because the average age of the longitudinal data substantially increases by excluding 2000. The coefficients of year dummies change, just because the reference point has shifted from 2000 to 2004. Only is the reversed effect of the aggregate variable of the community health infrastructure level hard to explain, mainly driven by data from the rural east. In addition, excluding the 2000 data increases magnitude of random effects, especially the individual-level variance. It suggests that unobserved variation in PHI prevalence increased after 2000, attributed predominantly to the individual level. For the disaggregated populations, the greatest community-level variance and the greatest individual-level variance still exist in the rural east and the rural inland, respectively, the same as those including the 2000 data. Likewise, the unobserved variation continues to be attributed more to the community level in the east, and more to the individual level in the inland.

In sum, the coefficient profiles of the models including or excluding the 2000 data are in effect more similar than different. It suggests that effects of most determinants of

PHI prevalence did not significantly change between 2000 and 2004, except the remarkably reversed SHI effects. Thus, for most determinants it is basically appropriate to fit such models based on the pooled longitudinal data, but the changing effects of SHI would be hidden. Separating some data from others by time, though essentially more suitable for cross-sectional data than longitudinal data, is a compromise here to protect relevant information from strong influence of the 2000 data.

Table 5.10 The models based on data excluding 2000

	Total	*Urban east*	*Rural east*	*Urban inland*	*Rural inland*
	Model 11	*Model 11a*	*Model 11b*	*Model 11c*	*Model 11d*
			Coefficient (S.D.)		
SHI	Reference = No SHI				
FMS	-1.23(0.20)***	-1.41(0.36)***	-0.95(0.30)**	-1.36(0.30)***	-1.35(0.64)*
Urban SHI	-1.79(0.15)***	-1.85(0.27)***	-2.28(0.24)***	-1.62(0.23)***	-1.24(0.34)***
NCMS	-1.18(0.14)***	-1.18(0.48)*	-1.40(0.20)***	-1.20(0.34)***	-1.63(0.28)***
Year	Reference = 2004				
2006	0.28(0.14)*	-0.62(0.33)ǂ	0.89(0.21)***	-0.02(0.21)	0.88(0.34)*
2009	1.00(0.15)***	0.36(0.30)	1.42(0.24)***	0.56(0.22)*	2.13(0.38)***
2011	1.27(0.17)***	0.22(0.35)	2.25(0.23)***	0.52(0.28)ǂ	2.31(0.39)***
Age	0.01(0.02)	-0.00(0.05)	0.01(0.03)	0.03(0.03)	-0.02(0.04)
Age^2	-3.50e-4(0.00)ǂ	-0.00(0.00)	-0.00(0.00)	-0.00(0.00)	-0.00(0.00)
Gender	-0.19(0.11)ǂ	-0.14(0.22)	-0.08(0.14)	-0.26(0.19)	-0.24(0.19)
Chronic diseases	0.21(0.12)ǂ	0.34(0.29)	0.11(0.19)	0.19(0.20)	0.28(0.23)
Household income	0.36(0.06)***	0.48(0.11)***	0.28(0.08)**	0.37(0.09)***	0.36(0.10)**
Household size	-0.13(0.04)**	-0.20(0.10)*	-0.15(0.05)**	-0.14(0.06)*	-0.09(0.05)ǂ
Education	Reference = None or primary school				
Middle or tech	0.29(0.12)*	0.22(0.32)	0.11(0.17)	0.38(0.25)	0.43(0.22)*
University	0.62(0.17)***	0.29(0.41)	0.47(0.32)	0.79(0.33)*	0.88(0.48)ǂ
Working	0.24(0.11)*	0.45(0.25)ǂ	0.27(0.17)	0.29(0.18)	-0.04(0.20)
Hukou	-0.41(0.15)*	0.07(0.43)	-0.45(0.22)*	-0.04(0.25)	-0.55(0.27)ǂ
Aggregate variables					
East	1.07(0.21)***				
Urban	0.91(0.26)***				
Population	0.05(0.07)	0.29(0.17)ǂ	0.20(0.13)	-0.05(0.13)	0.02(0.10)

Social services	0.03(0.02) ǂ	0.05(0.04)	0.01(0.03)	0.01(0.03)	0.06(0.05)
Health infrastructure	-0.07(0.02)**	-0.02(0.08)	-0.14(0.05)**	-0.00(0.06)	-0.04(0.04)
Random effect: Variance (S.D.)					
Community-level	1.34(0.21)***	0.88(0.13)***	2.26(0.60)***	0.99(0.35)**	0.88(0.33)**
Individual-level	1.92(0.29)***	0.32(0.13)*	1.63(0.33)***	2.14(0.50)***	2.26(0.50)***
Data source: CHNS (2004, 2006, 2009, 2011); N = 64,596. Significance values: ǂp≤0.10, *p≤0.05, **p≤0.01, ***p≤0.001.					

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